ON-JOB LEARNING AND HUMAN CAPITAL ACCUMULATION

A Dissertation
Presented to
The Academic Faculty

by

Qinyi Liu

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Economics

Georgia Institute of Technology
August 2018

ON-JOB LEARNING AND HUMAN CAPITAL ACCUMULATION

Approved by:

Dr. Haizheng Li, Advisor
School of Economics
Georgia Institute of Technology

Dr. Patrick S. McCarthy
School of Economics
Georgia Institute of Technology

Dr. Michael Kummer
School of Economics
Georgia Institute of Technology

Dr. Seung Hoon Lee
School of Economics
Georgia Institute of Technology

Dr. Barry Hirsch
Andrew Young School of Policy Studies
Georgia State University

Date Approved: [April 16th, 2018]

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisor, Prof. Haizheng Li, who has provided me with great help throughout the thesis with patience and knowledge while giving me room to work on my own. He has been always willing to help and prioritize students' needs no matter how busy his schedule is. I thank him not only for his professional academic support, but also for offering me so many opportunities to practice and grow. Because of his suggestions and encouragements, I started my experience of an academic life, gradually found my interests, and have decided to pursue an academic career after graduation.

I am also deeply grateful to Prof. Patrick McCarthy, Prof. Michael Kummer, and Prof. Seung Hoon Lee from Georgia Tech as well as Prof. Barry Hirsch from Georgia State University for serving on my Ph.D. committee. Their valuable comments and editions have given me a deeper understanding of channels of adult learning and skill dynamics, a new perspective on the empirical methods and interpretations of empirical results, and inspirations on the contributions of my study.

My sincere thanks also go to Peer Ederer, Prof. Zhiqiang Liu, Prof. Xiaojun Wang, Prof. Belton Fleisher, Prof. Barbara Fraumeni, and Prof. Calston Holz for their valuable comments and help. I would like to thank my parents and relatives for their continuous support that gave me strong incentives to persist during the PhD study. I also appreciate all the suggestions and help from my colleagues and friends. Special thanks to Lynn, Zekun, Xiyuan for their continuous support and help during my PhD study.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

The dissertation investigates the human capital accumulation through on-job learning. It has three empirical studies. The first two essays investigate skill accumulation through performing job tasks. The third one analyzes the labor market effect of tertiary education for full time workers.

Using the data from the Programme for the International Assessment of Adult Competencies (PIAAC) for USA, the first essay investigates whether cognitive skills, including literacy and numeracy skills, can be improved through on-the-job learning, especially via tasks at work. With rich information on job tasks performed at individual level, we construct different job complexity measures: a general job complexity measure, and two specific complexity measures of interactive and analytical tasks. The results show that workers can accumulate cognitive skills through solving complex problems. Additionally, analytical tasks play an important role on cognitive skills, while interactive tasks at work do not show a significant effect.

The second essay investigates whether tasks performed at work contribute to the improvement of a worker’s problem-solving skills. Based on two datasets for Germany, the Programme for the International Assessment of Adult Competencies (PIAAC) and “LLLight’in’Europe” project (LLL), we analyze on problem-solving skills at different levels, general problem-solving skills and complex problem-solving skills. The results of two problem-solving skill measures show workers benefit from doing a complex job, and task complexity improves complex problem-solving skills with a much smaller

magnitude. In addition, analytical tasks at work play a more important role than interactive tasks.

The third essay investigates the difference in effects of tertiary education between full-time workers and full-time students, based on data from the Chinese Household Income Project (1995, 2002, 2007, and 2013). We find that the schooling returns to a college and a graduate degree earned by full-time workers are significantly lower than the returns on corresponding degrees earned via full-time studies, however, there is a much smaller or no significant gap for junior college degrees for those two groups. The results are quite robust with different model specifications and estimation methods. Our further investigation shows that school quality or aging cannot explain the gap fully.

CHAPTER 1 INTRODUCTION: ON-JOB LEANRING

Human capital is accumulated through two main channels: schooling and on-job learning. On-job learning has various forms, it could be on-job learning-by-doing through performing tasks; it could be on-job schooling, i.e., working adults obtain a degree without quitting the job.

Job tasks have changed dramatically during the past 60 years. For example, Autor, Levy and Murnane (2003) found computerization increased non-routine problem-solving tasks and complex communication tasks from 1960 to 1998 in US. Similarly, Spitz-Oener (2006) suggests that occupations involve greater complexity over time, and have experienced a shift toward analytical and interactive activities and away from cognitive and manual routine tasks. The change in job tasks has raised the demands for high skilled workers that can solve the complex problems, and it also provides an important channel for workers to accumulate more skills through on-job learning.

However, there have been two problems in studying the effect of job tasks on a worker's skills. One is the lack of a good measure of job tasks, because on-the-job learning is usually measured using years of experience. This approach ignored the heterogeneity in on-the-job learning as workers with the same years of experience, even within the same occupation, may perform very different job tasks. Another one is the lack of measurement of a worker's skills.

Chapter 2 examines whether the workers can accumulate their cognitive skills through performing job tasks. We introduce the tasks at work into the traditional cognitive skill production function and use the the most recently available survey by OECD in 2012, the International Assessment of Adult Competencies (PIAAC) for the US to investigate this question. We use the combination of the two skills, including literacy skills and numeracy skills, to reflect a worker's cognitive skills instead. More specifically, we take the average of both scores and do the standardization.

Based on information on job tasks performed at individual level, we construct three job task complexity measures. One is a general job task complexity measure, and we consider a worker's job with a certain degree of complexity if he/she deals with those tasks at least once a month. We also have two detailed complexity measures of interactive and analytical tasks. More specifically, we create continuous interactive and analytical task measures through dividing the number of tasks performed by the worker with a frequency of at least once a week for each task, by the total number of work activities within each broad task category.

The difficulty in identifying the causal effect of job tasks on skills is due to the selection into complex job tasks by high-skilled workers. Therefore, to address the selection problem due to unobserved individual heterogeneity, various econometric techniques are applied to estimate the causal learning effect. We first relax the perfect proxy assumption and use tasks outside work as additional proxy for unobserved heterogeneity. We further relax the perfect proxy assumption and instead use tasks outside work as indicators for unobserved individual heterogeneity. We apply the multiple indicator approach using the job demand information. Considering the requirements for the IVs are quite strong, we combine the Multiple Indicator approach and IV approach, and use the detailed information on the unobserved heterogeneity to do a more efficient estimation.

Our estimates show a consistent story that workers can benefit from on-job learning through solving complex tasks at work. However, comparatively those effects of on-job learning through tasks are also much smaller than those from early investments.

Chapter 3 investigates how job tasks help improve a worker's problem-solving skills. This study uses tasks at work at individual level to investigate in more details about on-the-job learning. We use two survey data sets in Germany. The analysis primarily uses data from the Programme for the International Assessment of Adult Competencies (PIAAC) data (2012) organized by the OECD. The survey for the first time contains both a direct assessment of problem-solving skills (PS), and information on tasks performed at workplace at individual level. In addition to PIAAC, we also use a new survey data (2013) from the "LLLight'in'Europe" project (LLL), funded by the European Union. It contains information on higher level of problem-solving skill of an individual, i.e., complex problem-solving skills (CPS). The two datasets complement each other and allow this study to not only investigate how job tasks affect one's general problem-solving skills but also on complex problem-solving skills.

We also implemented multiple econometric techniques to address the selection into tasks by high-skilled workers. Our results consistently show that the complexity improves a worker's problem-solving skills. More specifically, the general task complexity plays an important role in improving an individual's problem-solving skill. Additionally, analytical tasks contribute the accumulation of problem-solving skills, while interactive tasks do not have a significant effect. Moreover, task complexity can also contribute to complex problem-solving skills but with a much smaller magnitude of effects, which implies that CPS are more difficult to accumulate.

Chapter 4 evaluates the difference in labor market effects for tertiary degrees obtained by those who are full-time workers compared to those who are full-time students. We used four waves of national representative survey data from the Chinese Household Income Project (CHIP) in 1995, 2002, 2007, and 2013 in the investigation. Based on both the macro and microdata, we describe the features of on-job education and demographic characteristics of individuals who chose it.

We estimate and discuss our empirical model for comparing labor market outcome between on-job schooling and regular schooling. We address the unobserved heterogeneity, and implement the proxy variable approach and control function approach to check the robustness of our baseline results. Our study finds a significant difference in the return to schooling between regular students and on-job students at college and graduate level, while the difference is insignificant at junior college level. Then we further investigate the potential causes for the gap between regular and on-job education. Based on the empirical estimates on schooling returns, we also do a cost-benefit analysis on the on-job education choice. It seems that there would be a trade-off for an individual to choose on-job tertiary education. On the one hand, a higher degree obtained while at work raises the earnings, and thus, the earlier a higher educational degree is obtained on-job, the higher lifetime income would be.

The dissertation makes several contributions to the current literature. Firstly, previous literature mostly used job tasks as proxy for a worker's human capital, but our research has a clear distinction between job tasks and skills. The thesis contributes to the literature and compares the learning effect of three different types of skills: problem solving skills, literacy skills and numeracy skills. These skill measures have not had sufficient assessments available for working adults. Furthermore, previous research uses overall experience and occupation types to capture on-job learning. However, job tasks vary substantially between and within occupations. We use individual level tasks performed at work as a more accurate measure of on-job learning. Lastly, we adds to the literature by investigating the difference between on-job schooling and regular full-time schooling in China.

The rest of dissertation is structured as follows: Chapter 2 analyzes the question whether the job tasks can improve cognitive skills. Chapter 3 presents the relationship between job task complexity and problem-solving skills. Chapter 4 investigates the labor market effect of tertiary education for full-time workers. Chapter 5 concludes.

CHAPTER 2 CAN JOB TASKS IMPROVE COGNITIVE SKILLS?

2.1 Introduction

It is believed that cognitive skills of the labor force are important for economic growth, innovation, and for individual success as well. Hanushek and Woessmann (2008) provides empirical evidence that the cognitive skills of the population—rather than mere school attainment—are powerfully related to individual earnings, to the distribution of income, and to economic growth. Other existing research, such as Hanushek and Kimko (2000), and Hanushek and Woessmann (2011), also show a strong relationship between cognitive skills and difference in long-run growth performance across OECD and non-OECD countries. For the US, Hanushek, Ruhose and Woessmann (2017) finds that the differences in knowledge capital account for 20-30 percent of the state variation in per capita GDP, with roughly even contributions by school attainment and cognitive skills. In additoin, studies, such as Rivera-Batiz (1992), Dougherty (2003), and Ferrer, Green and Riddell (2006), found that cognitive skills are positively correlated with the likelihood of employability and earnings. According to Hanushek and Woessmann (2015), cognitive skills are the “basic skills” that the governments should put great emphasis on in the new digital era.

There have been a series of theoretical and empirical research on nurturing those cognitive skills at different stages of life, and Heckman and Kautz (2013) provides a good review on them. Previous research analyzed the effect of different interventions at the early childhood, adolescents and young adults on cognitive skills. They argued that cognitive skills are stable in the early adulthood and focus on the role of education, to name a few, Cascio, Clark and Gordon (2008) , Ammermueller and Pischke (2009).

However, limited studies have examined the development of those cognitive skills at adulthood. Can these skills be still improved in adulthood? When individuals start working, on-the-job learning is considered to be a main channel for workers to accumulate their skills. Is it possible for adults to accumulate those skills through learning-by-doing via various tasks performed at work?

Therefore, we introduce the tasks at work into the traditional skill production function and use the the most recently available survey by OECD in 2012, the International Assessment of Adult Competencies (PIAAC) for the US to investigate those questions. If workers can accumulate the cognitive skills through learning by doing at work, it can provide interesting policy implications on life-long learning.

Work life and tasks have changed dramatically during the past 60 years. Rapidly growing technological advances are making the need for cognitive skills like literacy and numeracy skills more critical in workplaces. Studies show a rising relative demand on the jobs intensive in complex tasks and also higher requirements on skills. For example, Autor, Levy and Murnane (2003) finds computerization increased the labor inputs in non-routine problem solving and complex communication tasks.

Previous literature (e.g., Gathmann and Schönberg (2010); Autor and Handel (2013)) implicitly treat job tasks as measures for unobserved worker skills/human capital. However, the direct relationship between individual level tasks and cognitive skills remains to be not fully empirically justified and the inner mechanism is still unrevealed. This study follows Yamaguchi (2012) in making a clear distinction between worker skills and job tasks and investigates how job tasks improve cognitive skills. Yamaguchi (2012) points out that the observed task complexity is different from unobserved human capital.

Because of data limitation, the majority of existing research constructed task measures at work by mapping the aggregate occupation level task characteristics to micro data based on occupational code. For example, Yamaguchi (2012) represents the technology of skill formation by a linear function of work task complexity at occupational level, worker current skill level, other personal characteristics and skill shocks. However, aggregate task measures at occupational level act as an imperfect measure of learning by doing through tasks at work at individual level. For example, Autor and Handel (2013) uses individual level task investments or efficiencies at work as proxies for a worker's human capital stock, and finds worker-level task measures are powerful predictors of wages when occupation-level job tasks are simultaneously included in wage model. This study indicates that some acquired skills are from work tasks at individual level. To the best of our knowledge, our study is the first to investigate the accumulation of cognitive skills based on-the-job tasks performed at individual level. We go further to investigate whether and how such skills can be accumulated via performing different tasks at work.

2.2 Measurements on Cognitive Skills and Job Tasks

Our data is from the International Assessment of Adult Competencies (PIAAC). The first round of PIAAC survey took place from August 2011 to March 2012 in 23 participating countries from OECD. In each country, the PIAAC surveyed more than 5,000 individuals.[1] It provides information on education and work experience, and how adults use skills at work and at home. The data have been used in previous studies, for example, by Hanushek, Schwerdt et al. (2015) and Hanushek, Schwerdt et al. (2017).

Although the PIAAC data are available for many countries, it is quite restrictive to pool countries together to run one regression model, given the vast differences in labor market and work institutions. Instead, we conduct a country level study, and select the United States to study the existence of on-the-job learning through tasks at work. The US is considered to rely on the general education to prepare young people for work (Freeman and Schettkat 2001), so the cognitive skills are thought to be mostly accumulated in school. We are particularly interested to know whether the US workers can accumulate cognitive skills at work.

Our PIAAC sample includes full-time employed workers whose age ranges from 16 to 60. The samples work in industries such as manufacturing, construction, service and trade industries.[2] The average age is around 40.8 years old.[3] 52% of the US samples are female. The sample statistics for the PIAAC US sample are reported in Table 1.

[1] More details on the data could be found in the official website: http://www.oecd.org/skills/piaac/

[2] The PIAAC data has very detailed industry classifications. Because it is unlikely that worker's cognitive skills vary systematically across narrowly defined industries, we combine them into broader categories as manufacture/construction and service/trade to save degree of freedom, and add them in the regressions to capture industry-specific fixed effects on workers' cognitive skills. A more detailed classification of industry fixed effects does not change the results in any significant way.

Table 1 – Variable Definition and Summary Statistics-PIAAC USA

Variables	**Definitions**	Obs	Mean	Std. Dev.	Min	Max
Experience	Total number of years with paid work	1831	21.26	11.76	0	47
Years-current employer	Years worked for the current employer	1828	8.53	7.89	0	45
Middle school or below	1 if middle school education or below	1831	0.03	0.16	0	1
High school	1 if high school diploma	1831	0.33	0.47	0	1
College	1 if college degree	1831	0.45	0.50	0	1
Master or above	1 if master degree or above	1831	0.19	0.39	0	1
Female	1 if female	1831	0.52	0.50	0	1
Age	Age	1831	40.75	11.86	17	62
Mother with tertiary education	1 if mother's highest education is college or above	1831	0.31	0.46	0	1
Father with tertiary education	1 if father's highest education is college or above	1831	0.33	0.47	0	1
Manufacturing industry	1 if manufacturing, electricity supply, water supply, construction, etc.	1831	0.19	0.39	0	1
Service, Trade industry	1 if wholesale, retail trade, accommodation, financial and insurance, education, etc.	1831	0.81	0.39	0	1

Source: the International Assessment of Adult Competencies (PIAAC), 2012, USA

Education is measured by the highest education qualification obtained reported by workers.[4] In USA, the primary school lasts 5 years, followed by 7 years of junior and senior high school education in the similar type of schools, regardless of the student's academic performance (Gansow 2002, Deming and Figlio 2016). 45% of our sample obtained the highest degree at college level or above, and 33% of them have a high school degree.

[3] The age information is only available in categories grouped in 5 year intervals; we used the middle value for each category.

[4] The PIAAC follows the International Standard Classification of Education (ISCED) 1997.

As for the work history, the average year of experience is 21.[5] Workers' tenure in the current job is 8.5 for US workers on average.[6] They raise an interesting question on the learning dynamics on the job: will workers be able to improve cognitive skills through learning by doing within the current job? We will explore this question in the regression analysis below.

2.2.1 Cognitive Skill Measures

Hanushek and Woessmann (2008), Cascio, Clark and Gordon (2008) and Hanushek and Woessmann (2011) gave a comprehensive review on the different available measurement tests on cognitive skills, including literacy, numeracy, science skills. The cross-country datasets widely used are the Trends in International Mathematics and Science Study (TIMSS, sponsored by the International Association for the Evaluation of Educational Achievement), The Progress in International Reading Literacy Study (PIRLS, an assessment of reading comprehension of nine-year-olds in 35 countries and was conducted by the International Association for the Evaluation of Educational Achievement), and the OECD Programme for International Student Assessment (PISA). These surveys focus on students who are teenagers or younger. Three large-scale assessments have been conducted to measure the information-processing skills of populations aged 16–65 in different countries. They include the International Adult Literacy Survey (IALS), the Adult Literacy and Life Skills Survey (ALL), and the most

[5] The PIAAC asks workers to report how many years they have had paid work which includes the years with 6 months or more spent in either full-time or part-time work.
[6] The current age and the age the workers started working for the current employer are available in the data, we calculate the tenure with the current employer based on their difference.

recently available survey by OECD, the International Assessment of Adult Competencies (PIAAC).

Here we use the PIAAC dataset for working adults and focus our analysis for USA. PIAAC provides direct measures of cognitive skills of adults. In the PIAAC survey the literacy skill scores (LS) reflect the ability to understand, evaluate, use, and engage with different types of written texts, e.g. sentences, words in graphs, in both print-based and digital texts, and extend beyond understanding the texts to using the texts appropriately.[7] Their numeracy skills(NS) evaluates the ability to access, use, interpret, communicate mathematical information and ideas in real life activities, and extend beyond numbers and quantity to include things like dimensions, shapes, patterns, and relationships (OECD 2012).[8]

The test for skills ranges 0-500 points in the PIAAC survey, with higher points representing higher level of skills.[9] The summary statistics are reported in Table 2.

[7] The samples of literacy items in PIAAC include: highlighting the information on the latest time that children should arrive at preschool according to the preschool rules provided; choose the equipment that receives the largest number of ineffective ratings based on the physical exercise equipment chart, etc. In addition, the literacy framework for PIAAC also includes a new reading component assessment on vocabulary, sentence processing and basic passage comprehension to provide more information on the abilities of those with low levels of literacy.

[8] Numeracy items vary by complexity. Examples include typing in the numerical response of the temperature based on the graph of a thermometer; multiple choice question where individuals are required to choose one or multiple periods with a decrease in number of births based on the graph on dynamic trend of number of births provided; answering questions on number of wind power stations needed to replace the power generated by the nuclear reactor based on the statistics provided.

[9] In the whole paper, we use the average of 10 plausible values of the PIAAC scores in each domain.

Table 2 – Measures of Cognitive Skills-PIAAC USA

Definitions	Obs	Mean	Std. Dev.	Min	Max
Score for cognitive skills(CS)	1831	279.6	42.2	147.6	391.4
Score for literacy skills(LS)	1831	285.6	40.7	150.4	389.5
Score for numeracy skills(NS)	1831	273.7	46.2	128.6	416.0
Correlation Matrix	Cognitive skills	Literacy skills	Numeracy skills		
Cognitive skills	1.0				
Literacy skills	0.97	1.0			
Numeracy skills	0.98	0.89	1.0		

Sample Distribution	Numeracy skills			
Literacy skills	0th-25th	25th-50th	50th-75th	75th-100th
0th-25th	19.7%	4.9%	0.4%	0.0%
25th-50th	4.6%	13.2%	6.6%	0.7%
50th-75th	0.7%	6.3%	12.1%	5.9%
75th-100th	0.0%	0.6%	6.0%	18.4%

Note: the percentage above represents the share of sample with a skill score at a specific percentile level in the total sample. For example, 19.7% in the total sample have both the numeracy and literacy test scores at the 0-25th percentile.

In the regressions, we transform it into z-values for analysis purpose. To summarize, those two skills are closely correlated, and the correlation between the scores for the literacy skill test and numeracy skill test is 0.89 in our sample. They yet measure quite different domains of cognitive skills. For example, among working adults with a numeracy test score at the 50th-75th percentile, 7.0% have a literacy test score that is at the 50th percentile or lower. The corresponding number for the numeracy test score is also 7.0%.

We use the combination of the two scores to reflect a worker's cognitive skills instead, more specifically, we take the average of both scores and do the standardization, similar to Cunha and Heckman (2007) and Todd and Wolpin (2007) in their treatments of cognitive tests in PIAT and AFQT. The correlation coefficient between the overall measure of cognitive skills and literacy (numeracy) skills is 0.97(0.98). In the US samples, the average score of the skills is 279.6 points for CS; for separate skill measures, it's 285.6 points for LS, and 273.7 points for NS.

2.2.2 Job Task Measures

Instead of measuring learning by task characteristics at the occupational level as done in earlier literature, we use the information on tasks performed at individual level to reflect learning at work, and characterize jobs based on task complexity. In the PIAAC survey, one specific question relates to the overall complexity of tasks for a job. The question asks the worker to report the frequency of complex tasks at work; in particular, they take at least 30 minutes to think of a good solution. We consider a worker's job as complex if he/she deals with such task for at least once a month.

Moreover, a job is composed of a variety of tasks at different levels of complexity. In general, tasks can be categorized into two types, cognitive tasks, and manual/motor tasks, see for example Autor, Levy and Murnane (2003), Yamaguchi (2012). A cognitive task requires substantial cognitive activity, such as decision-making, problem-solving, memory, attention and judgement (Klein 1999). Cognitive tasks can be further divided into routine cognitive tasks, non-routine analytical tasks, and non-routine interactive/interpersonal tasks.[10] Routine cognitive tasks are characterized as codifiable, repeating, structured, and following explicit procedures, such as calculating, bookkeeping and correcting texts/data. Non-routine analytical tasks usually involve work activities of analyzing data/information, thinking creatively, and interpreting information for others,

[10] See for example Autor, Levy and Murnane (2003), Spitz-Oener (2006), Borghans, Ter Weel and Weinberg (2008), Gathmann and Schönberg (2010), and Acemoglu and Autor (2011), and Autor and Handel (2013).

such as researching, planning, designing, or evaluating. Non-routine interactive tasks include establishing and maintaining personal relationships, guiding, directing and motivating subordinates.

In the PIAAC survey, workers are asked how frequently they perform each one of the forty different tasks in their job.[11] Following the discussion above, those tasks can be generally classified as interactive or analytical tasks.[12] A job combines those two types of tasks in various ways that reflect job heterogeneity and complexity.

In order to integrate the information on multiple tasks within a broad task category together, some studies used principal component analysis (PCA), for example, Autor, Levy and Murnane (2003), Yamaguchi (2012), and Acemoglu and Autor (2011). However, PCA limited in the information integration of work tasks. PCA has no explicit interpretation based on individuals' behavior; the literature usually uses the first principal component that accounts for the largest variability in the data, however, the other lower variance components may also be important for the topic of interest.

[11] One might be concerned that the task complexity may not be an accurate measure of current job tasks performed because it's a realized equilibrium of job tasks and worker skills. However, there is a great skill mismatch in the job market and no perfect selection between jobs and skills. Not all workers are assigned to jobs in which their skills are sufficient or required at work; it has been supported by the research on the skill mismatch phenomenon in the labor market. For example, Manacorda and Petrongolo (1999) used data on 11 OECD countries to show increases in skill mismatch or skill upgrading in a few OECD countries including Germany in the 1980s. Manacorda and Manning (2007) also found a greater skill mismatch based on labor force shares and wages by education group in 1980s and 1990s in Germany. Likewise, using the PIAAC data, in Pellizzari, Fichen (2017) the skill well-matched ratio in literacy is 0.67 in Germany; the ratios in numeracy is 0.653.

[12] We drop a few tasks that may not be directly related to work, for example, work tasks of reading books; reading newspapers or magazines; writing articles for newspapers, magazines or newsletters; planning your own activities; organizing your own time at work. Or, it cannot help measure the job task complexity, e.g., how often workers usually faced by relatively simple problems that take no more than 5 minutes to find a good solution.

In the PIAAC survey, the information on tasks is similar to that in the German Qualification and Career Survey (GQCS).[13] Spitz-Oener (2006) and Black and Spitz-Oener (2010) construct direct measures of tasks based on the activities people perform on the job, i.e., the number of representative activities performed by the individual within the task category divided by the total number of activities in that task category. Similarly, Gathmann and Schönberg (2010) assume workers spend an equal amount of time on each task they performed at work, and calculate the average share of time spent on tasks at the occupational level for measurement of task-specific human capital.

Our definition is closely related to both Yamaguchi (2012), which measures task complexity at work, and Spitz-Oener (2006), which measures the shares of time workers spent performing different types of tasks at work, but we develop a job task measure with a combination of the information on both task complexity and task frequency. In particular, we have two different measures of task complexity: a general complexity measure and two detailed complexity measures on interactive and analytical tasks. We create continuous interactive and analytical task measures by dividing the number of tasks performed by the worker with a frequency of at least once a week for each task, by the total number of work activities within each broad task category.

Compared to principal component analysis, our measures have a clearer behavior interpretation. We evaluate the task complexity based on the share of tasks performed within a broad task category. For example, analytical tasks at work could be more

[13] The respondents in the GQCS Survey are asked whether they perform any of 19 different tasks in their job and whether it's their main activity. It's different from the DOT and O*NET data in that in DOT and O*NET, many variables do not have a natural scale and cannot be confidently be treated as cardinal. For example, in DOT, the variable DATA measures the complexity of tasks in relation to information, knowledge, and conceptions by integers from 0 to 6. O*NET has information on work activities, and work context importance scales.

complex if workers deal with multiple analytical tasks such as budgeting and coding together.

For the definition of the interactive tasks at work, we first select 13 tasks such as advising, making speeches, instructing or training people for the interactive task category. A worker is considered to frequently perform an interactive task at a certain degree of complexity if he/she performs more tasks among the 13 tasks, with the frequency of at least once a week for each of them.

Similarly, for the analytical task category, we include 18 detailed work tasks, such as writing a report; calculating prices, costs or budgets, programing; etc. We consider a worker performing a complex analytical task frequently, if he/she is involved in a higher percentage of tasks among the 18 tasks for at least once a week for each task. The detailed work tasks for each category are listed in Table 3.[14]

[14] One might be concerned that we treat the analytical task of reading diagrams, maps or schematics and the analytical task of using a programming language or write computer code as identical to define the complexity of analytical tasks. One might think that the later one is more complex than the first one, but that's not necessarily so. A task could be considered complex if it's operated by skilled workers and involve a lot of analytical thinking, for example, in PIAAC samples, a large share of production managers reads diagrams, maps or schematics to do important production decision making, while information and communication professionals and technicians do coding work more often. The same argument applies to the usage of ICT equipment at the workplace, such as using word processor or spreadsheet software.

Table 3 – Tasks at Work-PIAAC

Interactive tasks at work:	
1	Time cooperating or collaborating with co-workers
2	Sharing work-related information with co-workers
3	Instructing, training or teaching people, individually or in groups
4	Making speeches or giving presentations in front of five or more people
5	Advising people
6	Planning the activities of others
7	Persuading or influencing people
8	Negotiating with people either inside or outside your firm or organization
9	Use email
10	Read letters memos or emails
11	Write letters memos or emails
12	Selling a product or selling a service
13	Participate in real-time discussions on the internet, for example online conferences, or chat groups
Analytical tasks at work:	
1	Read directions or instructions
2	Read professional journals or scholarly publications
3	Read manuals or reference materials
4	Read bills, invoices, bank statements or other financial statements
5	Read diagrams maps or schematics
6	Write reports
7	Fill in forms
8	Calculating prices, costs or budgets
9	Use or calculate fractions, decimals or percentages
10	Use a calculator, either hand-held or computer based
11	Prepare charts graphs or tables
12	Use simple algebra or formulas
13	Use the internet in order to better understand issues related to your work
14	Use spreadsheet software, for example Excel
15	Use a word processor, for example Word
16	Use advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques
17	Conduct transactions on the internet, for example buying or selling products or services, or banking
18	Use a programming language to program or write computer code
Excluded tasks at work	
1	Usually faced by relatively simple problems that take no more than 5 minutes to find a good solution?
2	Working physically for a long period?
3	Using skill or accuracy with your hands or fingers?
4	Planning your own activities?
5	Organizing your own time?
6	Read books
7	Read newspapers or magazines
8	Write articles for newspapers, magazines or newsletters

Note: The PIAAC asks how often individuals perform the type of task in their job. The options include: 1 Never; 2 Less than once a month; 3 Less than once a week but at least once a month; 4 At least once a week but not every day; 5 Every day. The options for “Time cooperating or collaborating with co-workers?” are: 1 None of the time; 2 Up to a quarter of the time; 3 Up to half of the time; 4 More than half of the time; 5 All the time.

The descriptive statistics of the task measures are reported in Table 4. It shows that overall 77% of the US workers deal with complex tasks that take at least 30 minutes to find a good solution for at least once a month. Additionally, US workers reported that they are frequently involved in 57% of 13 interactive tasks for at least once a week, and 45% of 18 analytical tasks on average.

Table 4 – Tasks at Work-PIAAC USA

Variables	**Definitions**	Obs	Mean	Std. Dev.	Min	Max
Complex task at work	1 if confronted with more complex problems that take at least 30 minutes to think of a good solution at least once a month at work	1831	0.77	0.42	0	1
Interactive task at work	Share of tasks that performed at least once a week among 13 interactive tasks at work	1831	0.57	0.21	0	1
Analytical task at work	Share of tasks performed at least once a week among 18 analytical tasks at work	1831	0.45	0.22	0	1

2.3 Cognitive Skills, Education, and On-the-job Learning

2.3.1 Production Function of Cognitive Skills

Cunha, Heckman, Schennach (2010) formulates and estimates multistage production functions for children's cognitive skills, which are determined by parental environments and investments at different stages of childhood. Based on their framework, to analyze the formation of cognitive skills, we describe how skills evolve over time in a two period model: For period 0, each individual is endowed with initial cognitive skill stocks CS_0 before he/she enters labor market. For period 1, the individual starts working, followed by multiple jobs t. The stock of cognitive skills at job t is determined by:

$$CS_t = f_t(CS_0, I_1, ..., I_t, a_t), t = 1, 2, ..., n \quad (1)$$

where CS_t denotes the vector of cognitive skill stocks at job t. I_t denotes the on-the-job investments at job t. Cognitive skills will depreciate with age so the current age in job t a_t is also included. One crucial channel is learning by doing at the work place, mainly in the form of dealing with tasks at work.

Our research focus is to investigate how the tasks would affect the formation of cognitive skills. Workers are engaged in dealing with various types of tasks either individually or through group work. Workers are supposed to learn through tasks at work in the following way: the learners will develop literacy and numeracy skills, and are most likely to transfer their learning to new contexts, where workplace teaching and learning opportunities engage them in solving real tasks, and support the learners to articulate their own use of strategies for dealing with tasks. Therefore, based on the previous analysis, we specify that on-the-job learning in job t is not only measured through years of job experience ew_t but also job tasks performed w_t:

$$I_t = \{ew_t, w_t\} \quad (2)$$

We assume that tasks performed at the current job could be represented by a function of tasks performed in previous jobs and the corresponding job tenures, i.e., current input measures capture the entire history of inputs, $w_t = g(w_1, w_2, ...w_{t-1}; ew_1, ew_2, ..., ew_{t-1}, ew_t)$. Then with simplified assumptions on the function form, the cognitive achievement production function through job tasks could be written as:

$$CS_t = \lambda CS_0 + f_h(w_t; ew_1, ew_2, ..., ew_t)\beta + \delta a_t. \quad (3)$$

Furthermore, when the specific job tenure at each previous job is missing we use the number of jobs worked t and the cumulative work experience ex_t to proxy the tenure for each job $ew_1, ew_2, ..., ew_t$. We also consider the case that the current job tenure reflects the quantity of learning at the current job and affects the cognitive skill accumulation through current job tasks, and then we get the new model:

$$CS_t = \lambda CS_0 + f_h(w_t, ew_t; t, ex_t)\beta + \delta a_t. \quad (4)$$

Thus, skill accumulation can be represented by the tasks of current job, the tenure of the current job, the total number of jobs, and the overall length of work experience. Based on the previous analysis, we then obtain the model as below:

$$CS_t = \lambda CS_0 + w_t\beta_1 + (ew_t \cdot w_t)\beta_2 + \beta_3 t + \beta_4 ex_t + \delta a_t. \quad (5)$$

Assume that the initial skill endowment at the labor market entry CS_0 is composed of observed components and unobserved components, as discussed in the extensive educational production function literature (Hanushek 2002), these initial cognitive skills CS_0 are affected by a range of factors including schooling inputs(S), family inputs (F), inherited individual ability (q), and other relevant factors (Z). Therefore, we have:

$$CS_0 = S\kappa_1 + F\kappa_2 + Z\kappa_3 + q \qquad (6)$$

Based on that, we have the empirical model as follows:

$$CS_t = w_t\beta_1 + (ew_t \cdot w_t)\beta_2 + \beta_3 t + \beta_4 ex_t + \beta_5 ex^2{}_t + \lambda S\kappa_1 + \lambda F\kappa_2 + \lambda Z\kappa_3 + \delta a_t + q + u\ , \quad (7)$$

where in this specification, w_t represents a $1\times n$ vector of different tasks at work, [w_{1t}, $w_{2t}\ldots$,w_{nt}]. The marginal effects of tasks at work are represented by β_1. β_2 captures the dynamic learning process in the current job. ex denotes the years of total labor market experience. The human capital production model includes labour market experience and its quadratic form which captures the obsoletence of skills with experience. The observed components of initial cognitive skills are as follows: S reflects the investments in schooling, which is captured by the highest education degree obtained. F represents family investments, which is reflected by parental education. Z includes other observed characteristics such as gender. q represents the unobserved component of initial skills, e.g., ability, motivation, preference, etc.; u is the idiosyncratic error term.

2.3.2 Distributions of Cognitive Skills

Based on the sample from the PIAAC data discussed above, we first draw the distribution of cognitive skills with education in Figure 1, and it shows that the skill scores increase with education, as expected. For example, the average score of cognitive skills is 223.3 points for those with an education of middle school or below but 286.5 points for samples with a college degree. The gap is 60 points for literacy skills, and 67 points for numeracy skills respectively.

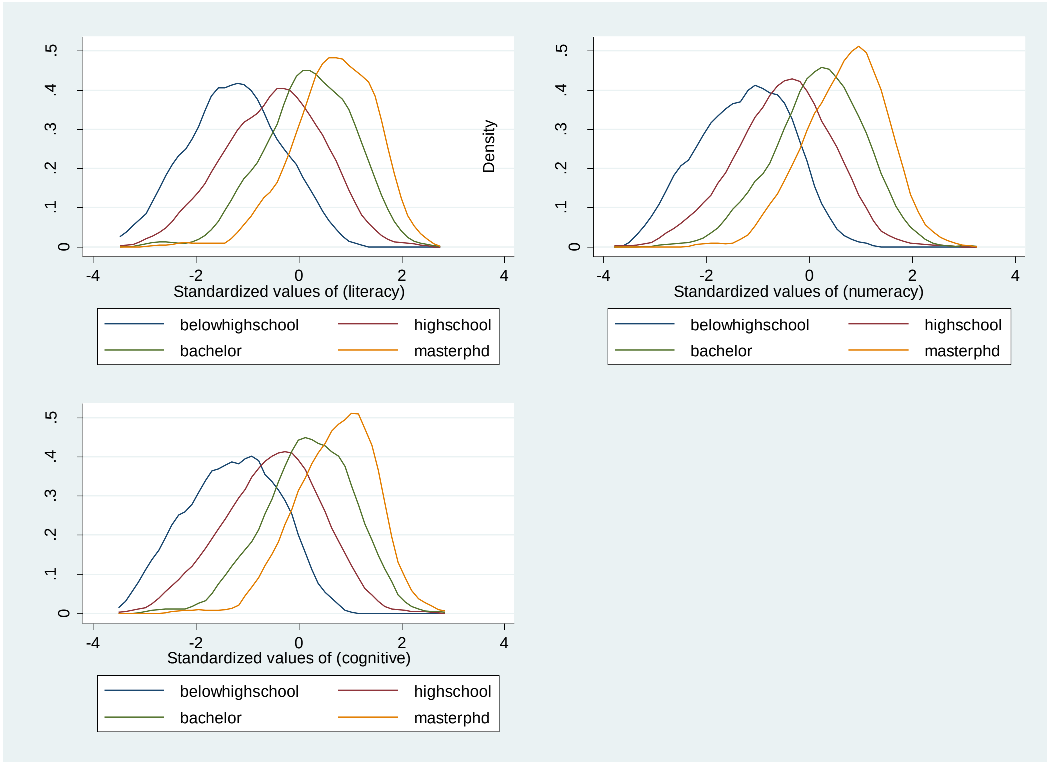
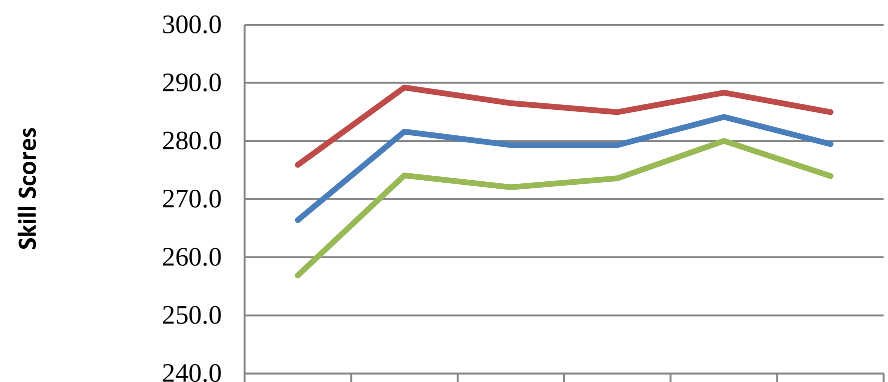


Figure 1 Distribution of Cognitive Skills with Education

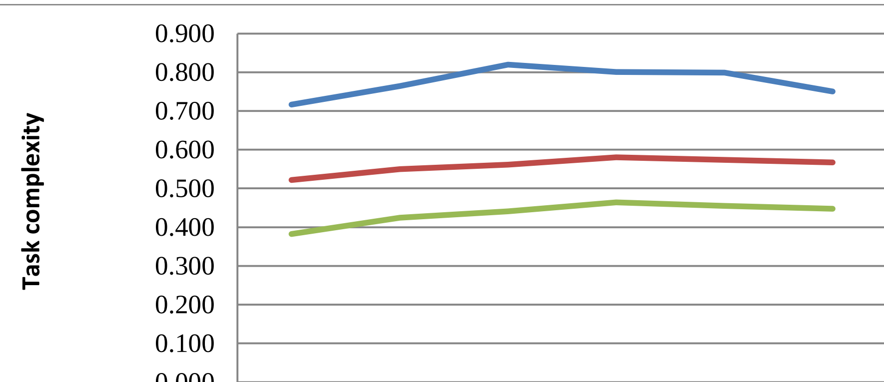
In order to see the learning dynamics at work, we list the average scores of overall cognitive skills, literacy skills and numeracy skills based on years of job experience. As shown in Figure 2, there is a nonlinear trend of LS and NS with work experience. The mean cognitive skill score of US workers with 4-7 years' experience is 15 points higher than the average score with 0-3 years' experience, then lowers a bit and eventually reaches the peak with an experience of 16-19 years and declines again. In details, the gap between workers with 4-7 years' experience and those with 0-3 years' experience is 13.3 points for literacy skills, and 17.2 points for numeracy skills. It indicates that both LS and NS can change with job experience. Two factors may play a role for the dynamic trend here: the first is on-the-job learning; and the other is the accompany effect of aging that reduce an individual's cognitive skills.



Total experience	0-3	4-7	8-11	12-15	16-19	20 or above
Cognitive skills	266.4	281.6	279.3	279.3	284.2	279.5
Literacy skills	275.9	289.2	286.5	285.0	288.3	285.0
Numeracy skills	256.9	274.1	272.1	273.6	280.0	273.9

Figure 2 Distributions of Cognitive Skills with Work Experience

However, years of job experience is a very general measure of on-the-job learning, because workers with the same number of work experience may perform quite different job tasks. As is shown in Figure 3 on the distributions of tasks with experience, the more experienced workers deal with relatively more complex job tasks. The increase in the complexity of job tasks happens mostly within the first 11 years' work experience and after that the job task complexity declines.



Total experience	0-3	4-7	8-11	12-15	16-19	20 or above
Complex task	0.717	0.764	0.820	0.801	0.799	0.750
Interactive task	0.522	0.550	0.561	0.580	0.574	0.567
Analytical task	0.382	0.424	0.441	0.464	0.455	0.448

Figure 3 Dynamics of Task Complexity with Work Experience

Next, we investigate how the tasks are related to the distribution of cognitive skills. The distribution of cognitive skills with job tasks is shown in Figure 4. We first compare the distribution of overall cognitive skills between workers who deal with complex tasks for at least once a month and those who do not. The gap in their mean is 0.44 standard deviation, which implies an increase in cognitive skills from 50^{th} percentile to 67^{th} percentile. However, the gap is much smaller than the gap between workers with a college degree and those with a high school degree, which is 0.69 standard deviation. Therefore, in comparison of Figure 1and Figure 4, we find that there is a much smaller effect of job task complexity on cognitive skills compared to that of general education.

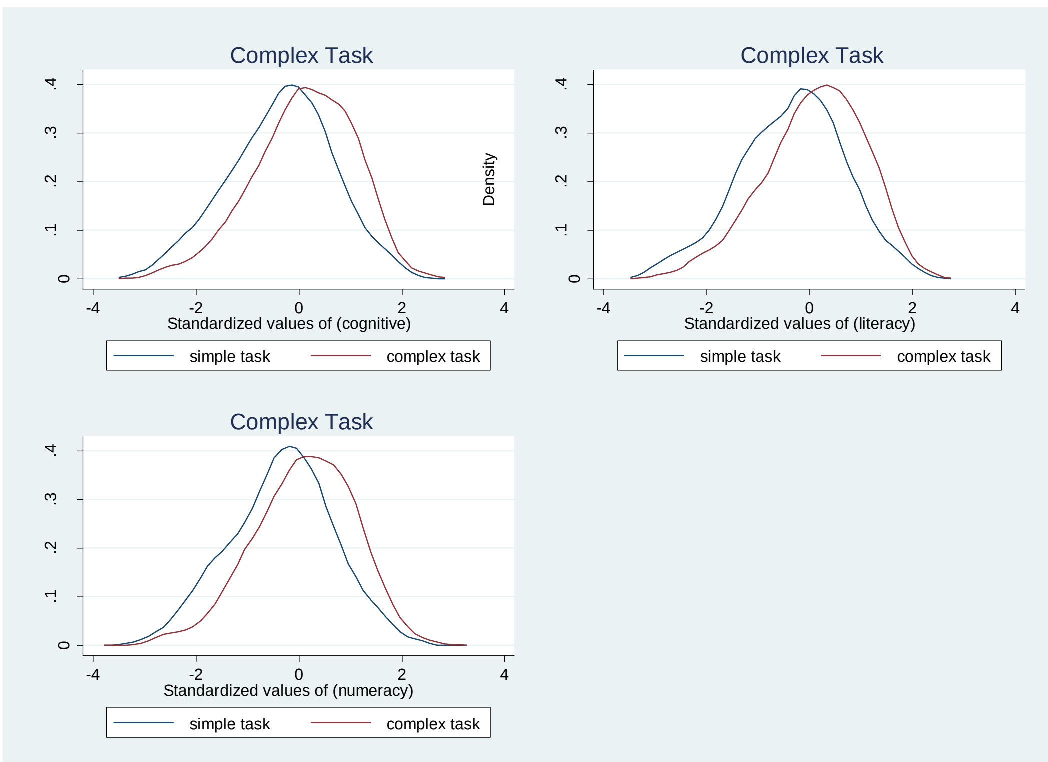


Figure 4 Distributions of Cognitive Skills with General Job Task Complexity

Figure 5 shows the distribution of cognitive skills with respect to interactive/analytical tasks. It seems that the gap for cognitive skills is mainly between workers who deal with a complex interactive task at work at the 0^{th}-25^{th} percentile and those at the 25th-50th percentile. More specifically, the gap is 0.28 standard deviation for interactive tasks, and 0.45 standard deviation for analytical tasks.

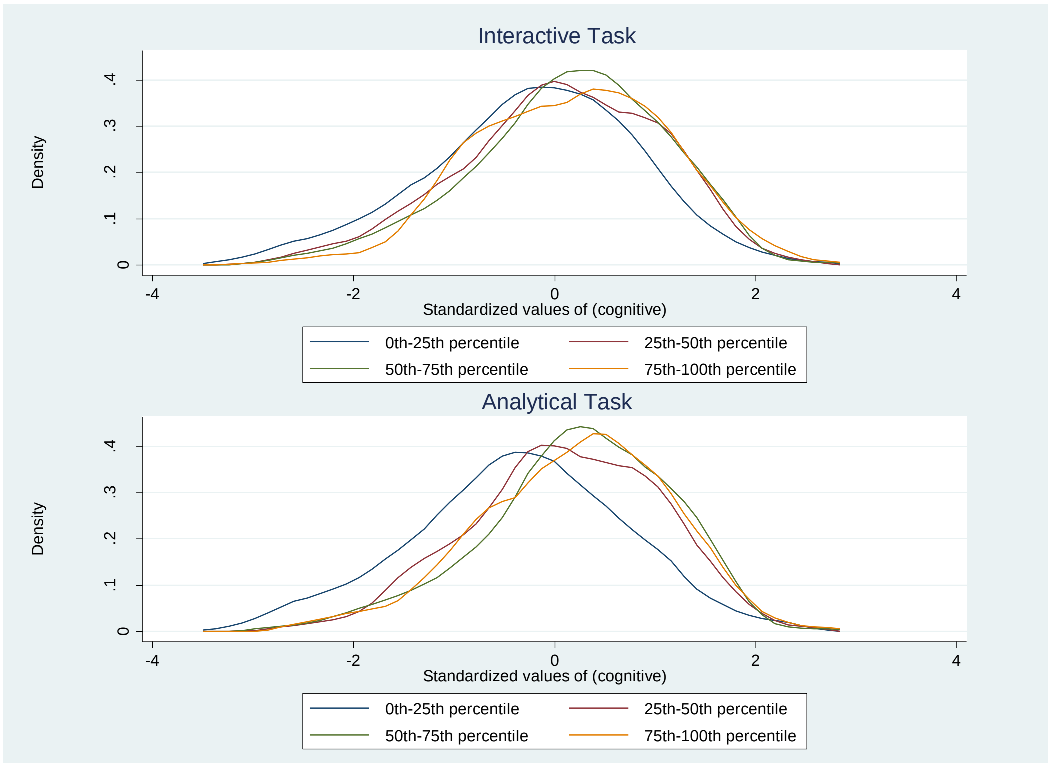


Figure 5 Distributions of Cognitive Skills with Specific Job Task Complexity

2.4 Baseline Results about the Effect of On-the-job Tasks on Cognitive Skills

Based on theoretical framework and the data, we estimate a simplified empirical model (8) as follows:

$$CS_t = w_t\beta_1 + \beta_3 ex_t + \beta_4 ex^2{}_t + S\kappa_1 + F\kappa_2 + Z\kappa_3 + \delta a_t + q + u \text{, (8)}$$

where the cognitive skill measurement CS is an average of two scores measuring different skills, i.e., literacy skills and numeracy skills. w is the vector of job tasks, and it includes three different measures of task complexity: a general complexity measure, and/or two detailed complexity measures for interactive and analytical tasks. q represents unobserved individual skill endowment, such as ability, motivation, preference, etc. It differs from model (7) in that we exclude the number of job change because such information is unavailable in the PIAAC data.[15] The job task complexity measure w_t will be endogenous when $Cov(w_t, q) \neq 0$. More specifically, workers with high ability q may either self-select into solving complex job tasks, or be assigned by employers to do that based on some individual traits unobservable by econometricians.

To address the omitted variable bias, in our baseline estimation, parent education is used to capture both the family investments F and the inherited ability from parents. Our benchmark results for cognitive skills are reported in Table 5. In the first column, we include the general complexity of tasks at work, and only interactive and analytical task in column 2, column 3 include all job task measures. The results show that job tasks all have a positive effect on cognitive skills. The result in the first column shows that the job task complexity has a positive and significant effect on cognitive skills. It indicates that when individuals deal with complex tasks at least once a month at work, their problem-solving skills are expected to be 0.18 standard deviation higher, i.e., workers at the 50th percentile move up to the 57th percentile in the sample distribution of CS.

With all task measures included in the third column, the effect of the general complexity measure is reduced in half but remains highly significant. Moreover, the general job task complexity still has the highest effect, i.e., when individuals solve complex problems for at least once a month at work, their cognitive skills are expected to

[15]We tried to add the information on the number of different employers/institutions he/she worked for within the past 5 years in the estimation. It shows no significant impact on the cognitive skills, and the effects of job tasks differs only in two decimal points.

have a 0.10 standard deviation increase, e.g., workers at the 50 percentile move up to be at the 54th percentile. It's followed by analytical task, and the result shows that with an additional 10% more involvement in 18 analytical tasks for at least once a week at work, workers have a 0.51 standard deviation higher CS. The interactive task has the smallest effect and it's not statistically significant.

Table 5 – Cognitive Skills & Tasks at Work-PIAAC USA

Dependent variable: Cognitive skills	(1)	(2)	(3)
Complex task at work	0.180***		0.0965*
	(0.0486)		(0.0535)
Interactive task at work		-0.00316	-0.00649
		(0.0110)	(0.0112)
Analytical task at work		0.0555***	0.0508***
		(0.0108)	(0.0112)
Experience	0.0347***	0.0341***	0.0340***
	(0.00892)	(0.00894)	(0.00893)
Experience squared/100	-0.0545***	-0.0555***	-0.0548***
	(0.0174)	(0.0174)	(0.0174)
High school	0.551***	0.526***	0.519***
	(0.130)	(0.126)	(0.127)
College	1.147***	1.104***	1.091***
	(0.130)	(0.127)	(0.127)
Master or above	1.618***	1.584***	1.564***
	(0.136)	(0.133)	(0.133)
Female	-0.269***	-0.260***	-0.257***
	(0.0412)	(0.0410)	(0.0410)
Mother with tertiary education	0.159***	0.161***	0.160***
	(0.0481)	(0.0483)	(0.0482)
Father with tertiary education	0.271***	0.260***	0.260***
	(0.0469)	(0.0472)	(0.0470)
age30_44	-0.211***	-0.207***	-0.208***
	(0.0702)	(0.0704)	(0.0704)
age45_59	-0.377***	-0.364***	-0.365***
	(0.0980)	(0.0977)	(0.0977)
Service industry	0.0454	0.0317	0.0387
	(0.0532)	(0.0532)	(0.0533)
_cons	-1.339***	-1.374***	-1.406***
	(0.144)	(0.141)	(0.143)
N	1831	1831	1831
adj. R^2	0.292	0.300	0.301

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The cognitive skills have a concave growth with experience. 10 year's increase in work experience increase a worker's cognitive skills by 0.34 std. dev. points (a rise of 13th percentile from the mean), and the cognitive skills start to decline with experience when workers have a work experience of 31 years.

The cognitive skills depreciate acceleratedly with age. More specifically, compared to workers aged 16-29, the skills start to decrease with an annual rate of 0.01 standard deviation for workers aged 30-44. In comparison, the annual depreciation rate for workers whose age range from 45-59 is 0.02 standard deviation on average.

As expected, our results show that workers with more education have higher cognitive skills. In particular, US workers with a high school degree, college degree, and master degree or above have 0.52, 1.09, 1.56 std. dev. points higher CS, when compared to those with a middle school degree or below. To put it in a different way, a person with cognitive skills at the 50th percentile can improve their skills to be at the 69.8th percentile when he/she obtains a high school degree, and the new rank would be the 86.2th percentile for a college degree, and the 94.1th percentile for a graduate degree. Furthermore, it's easy to find that the effect of a 4-year college education is much larger than that of 4 years' job experience, which is 0.12 standard deviation. This is consistent with Heckman and Kautz (2013)'s analysis that cognitive skills are easier to accumulate in early education.

The other estimates in the model are as expected in sign and significance. Parents' education plays a significant role in cognitive skill accumulation. More specifically, the cognitive skills of a worker whose father has a college education or above is 0.26 standard deviation higher than those whose father don't, and its magnitude is relatively larger than that of a mother's education, which is 0.16 standard deviation. Female workers have lower cognitive skills compared to male workers, and the gap is 0.26 standard deviation.

We also estimate a more general specification of the model (8) and investigate the the dynamic learning process in the current job by adding the interaction term between the current job task measures and the current job tenure. The years the employees worked for a particular employer could show the quantity of on-the-job learning with the task characteristics specific to the employer. However, the results in Table 6 provide no clear evidence on the existence of dynamic learning. The results in the first and second column imply that the current job tenure has a positive effect on the effects of job tasks on cognitive skills but the effect is statistically insignificant. There exists high collinearity between the interaction terms with current job experience, and the correlation coefficients range from 0.78-0.85. Therefore, since all the results from the more general models don't show qualitative difference from our previous results without the interaction terms, we focus on our further analysis on the more parsimonious model without the interaction terms.

Table 6 – Cognitive Skills & Learning Dynamics with Job Tasks-PIAAC USA

Dependent variable: Cognitive skills	(1)	(2)
Complex task at work	0.0764	0.0953*
	(0.0602)	(0.0534)
Interactive task at work	-0.00604	-0.00579
	(0.0112)	(0.0112)
Analytical task at work	0.0510***	0.0453***
	(0.0112)	(0.0122)
Complex task at work*current job experience	0.00242	
	(0.00322)	
Analytical task at work*current job experience		0.000691
		(0.000596)
Experience	0.0333***	0.0330***
	(0.00902)	(0.00903)
Experience squared/100	-0.0536***	-0.0536***
	(0.0175)	(0.0175)
High school	0.560***	0.560***
	(0.122)	(0.122)
College	1.135***	1.135***
	(0.123)	(0.123)
Master or above	1.608***	1.606***
	(0.129)	(0.129)
Female	-0.260***	-0.260***
	(0.0410)	(0.0410)
Mother with tertiary education	0.156***	0.157***
	(0.0481)	(0.0481)
Father with tertiary education	0.256***	0.257***
	(0.0469)	(0.0469)
age30_34	-0.211***	-0.212***
	(0.0712)	(0.0711)
age55_59	-0.383***	-0.387***
	(0.0984)	(0.0982)
Service industry	0.0375	0.0375
	(0.0532)	(0.0532)
_cons	-1.430***	-1.423***
	(0.140)	(0.141)
N	1828	1828
adj. R^2	0.302	0.303

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Tasks outside Work and Unobserved Heterogeneity

In the estimation of model (8), q represents unobserved individual skill endowments and preferences. Parental education can help partially control for it, but may not be sufficient. As a result, it is possible that the error term is still correlated with job tasks. Therefore, we incorporate additional information to address the unobserved heterogeneity problem here.

2.5.1 Tasks outside Work as Proxy

In order to find additional information that represents a worker's unobserved preferences, motivations, we explore further the data from PIAAC. The PIAAC survey asks workers to report how often they deal with tasks outside work. The activities outside work can be both an input for CS accumulation, similar to that of job tasks. It should also capture the individuals' unobserved preference toward job tasks because they are not mandatory or required to do such tasks outside work.

Following the similar procedure for tasks at work, we define the complexity of interactive tasks and analytical tasks outside work accordingly. In particular, among those 17 analytical activities outside work, we define the complexity of analytic tasks with the share of tasks performed with the frequency of at least once a week among 17 tasks. Similarly, we measure the complexity of interactive task with the share among the 4 ICT interactive activities outside work. The measurement of the interactive tasks outside work is based on 4 ICT tasks including online communications; email usage; reading letters, memos or emails; writing letters, memos, or emails. These tasks outside work are daily communications through emails and online chatting tools. It captures the unobserved ability/preference on usage of information and communication technologies, which lead to a higher skill scores assessed in the computer-based environment. The details on representative tasks are listed in Table 7.

Table 7 – Tasks outside Work-PIAAC

Interactive tasks outside work:	
1	Participate in real-time discussions on the internet, for example online conferences, or chat groups
2	Use email
3	Read letters memos or emails
4	Write letters memos or emails
Analytical tasks outside work:	
1	Read directions or instructions
2	Read manuals or reference materials
3	Read bills, invoices, bank statements or other financial statements?
4	Read diagrams maps or schematics
5	Fill in forms
6	Calculating prices, costs or budgets
7	Use or calculate fractions, decimals or percentages
8	Use a calculator, either hand-held or computer based
9	Use simple algebra or formulas
10	Prepare charts graphs or tables
11	Use the internet in order to better understand issues related to, for example, your health or illnesses, financial matters, or environmental issues?
12	Conduct transactions on the internet, for example buying or selling products or services, or banking?
13	Use spreadsheet software, for example Excel?
14	Use a word processor, for example Word?
15	Read professional journals or scholarly publications?
16	Read books, fiction, nonfiction
17	Read newspapers or magazines
Excluded tasks outside work	
1	Write articles for newspapers, magazines or newsletters
2	Write reports
3	Prepare charts graphs or tables
4	Use advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques
5	Use a programming language to program or write computer code?

Note: The PIAAC asks how often individuals perform the type of task in their job. The options include: 1 Never; 2 Less than once a month; 3 Less than once a week but at least once a month; 4 At least once a week but not every day; 5 Every day.

The USA samples report they deal with 65% of 4 ICT interactive tasks for at least once a week outside work, and they do approximately 39% of 17 analytical tasks outside work on average.

Therefore, to deal with the omitted variable bias, in the further estimation, the tasks outside work are used as proxy variables for unobservable. It produces consistent estimates assuming that tasks outside work act as a perfect proxy, i.e., redundant to the model if individual ability/preference/motivation is included, and is to purge the correlation between tasks at work and the unobservable q. A similar approach was adopted in Krueger (1993), which controls for whether workers use a computer at home and check whether the return to computer use at work is spurious.

In Table 8, column 1, we add analytical and interactive tasks outside work as proxy for individual heterogeneity q. With the tasks outside work controlled, the marginal effects of tasks at work don't change qualitatively but become smaller. In particular, workers who deal with a general complex task have 0.09 (a rise of 3.6 percentile) standard deviation higher cognitive skills. Also, analytical tasks at work will lead to an additional increase of 0.04 standard deviation.

Table 8 – Tasks at Work & Tasks outside Work-PIAAC USA

Dependent variable: Cognitive skills	Proxy Variable Approach	Multiple Indicator Approach
Complex task at work	0.0904*	0.0904*
	(0.0524)	(0.0520)
Interactive task at work	-0.0170	-0.0170
	(0.0110)	(0.0113)
Analytical task at work	0.0382***	0.0382***
	(0.0114)	(0.0115)
Experience	0.0322***	0.0322***
	(0.00868)	(0.00864)
Experience squared/100	-0.0485**	-0.0484**
	(0.0168)	(0.0167)
High school	0.497***	0.497***
	(0.129)	(0.128)
College	1.033***	1.033***
	(0.129)	(0.130)
Master or above	1.462***	1.461***
	(0.136)	(0.138)
Female	-0.291***	-0.291***
	(0.0404)	(0.0407)
Mother with tertiary education	0.164***	0.164***
	(0.0476)	(0.0474)
Father with tertiary education	0.237***	0.237***
	(0.0463)	(0.0469)
Interactive task outside work	0.0625***	0.0627**
	(0.00860)	(0.0191)
Analytical task outside work	0.000119	
	(0.0118)	
_cons	-1.626***	-1.627***
	(0.149)	(0.162)
Age dummies + Industry dummies	Yes	Yes
N	1831	1831
adj. R^2	0.326	
Analytical task outside work as instrument	-	0.574***
	-	(0.031)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As expected, interactive tasks outside work contribute positively to the growth of cognitive skills. In particular, 10% increase in the share among the 4 interactive tasks outside work lead to 0.06 (a rise of 2.4 percentile from the mean) standard deviation higher CS. It is consistent with our previous analysis that it captures the ICT related skills and preferences. However, analytical tasks outside work seem to have no significant effect on CS.

2.5.2 Tasks outside Work as Indicator

It is possible, though, tasks outside work are not perfect proxy for a worker's ability, and then all the OLS estimates would be inconsistent. Therefore, we relax the assumptions on tasks outside work as perfect proxy; instead we use them as indicators for an individual's unobservable and apply the Multiple Indicator (MI) estimation.[16]

The key assumption for the MI approach, as shown in the footnote, is $Cov(r_1, r_2) = 0$, which implies that the interactive tasks and analytical tasks outside work are not correlated after netting out the common factors such as the general ability, motivation, etc. This assumption is likely to stand because interactive tasks and analytical tasks represent very different personal characteristics after the general ability is excluded. Therefore, we use tasks outside work as indicators for the unobserved ability and apply the MI approach. Similar approach is applied in Blackburn and Neumark (1992) and

---

[16] If we have two indicators q_1 and q_2 for omitted ability q, we use multiple indicator approach to correct for the omitted ability bias in the model $y = w_t\beta_1 + \beta_3 ex_t + \beta_4 ex^2{}_t + S\kappa_1 + F\kappa_2 + Z\kappa_3 + \delta a_t + q + u$, where w, ex, S, F could be endogenous. Assume the indicators have a function form: $q_1 = \delta_0 + \delta_1 q + r_1, q_2 = \rho_0 + \delta_2 q + r_2$. After replacing q with q_1 or q_2, we would have the new model: $y = w_t\beta_1 + \beta_3 ex_t + \beta_4 ex^2{}_t + S\kappa_1 + F\kappa_2 + Z\kappa_3 + \delta a_t - \frac{\delta_0}{\delta_1} + \frac{1}{\delta_1} q_1 - \frac{1}{\delta_1} r_1 + u$. Under the assumptions of $cov(r_2, r_1) = 0$, $Cov(r_1, q) = 0$, $Cov(r_2, q) = 0$, i.e., after netting out the q, q_1 and q_2 are not correlated, we could use q_2 as instrument for q_1 because it satisfies $Cov(q_2, -\frac{1}{\delta_1} r_1 + u_1) = 0$ and $Cov(q_2, q_1) \neq 0$.

Wooldridge (2010), which used two intelligence test scores, IQ and Knowledge of the World of Work as indicators of ability to estimate the wage equation. Furthmore, the MI approach has less restrictive consistency assumption for other regressors; there is no need to assume zero correlations between other regressors and the remaining residual from tasks outside work.

Asymptotically, it is consistent to choose either interactive tasks or analytical tasks outside work as the indicator, but the results may differ in the finite sample.[17] The result in Table 8, column 2 shows that with the interactive tasks outside work as the included indicator, the marginal effects of job tasks remain unchanged compared to the result with the proxy variable approach. And analytical tasks outside work as instrument is closely correlated with the interactive tasks outside work based on its first stage coefficients.

2.6 Instrumental Variable Estimation with Job Demand-side Information

In the above estimations, the multiple indicator (MI) approach requires that the interactive tasks and analytical tasks outside work are not correlated netting out the common q that influences both of them. It is possible that, even after we control for all the ability indicators, the remaining error terms may still be correlated with other regressors. Therefore, we also apply the instrumental variable (IV) approach to the model.[18]

[17] We find some differences on the empirical results using different indicators in that when we use analytical tasks outside work as included indicator in the model, it will make the analytical tasks at work insignificant and interactive tasks at work negative significant.

[18] Another side concern is the multiple indicator approach may produce inconsistent estimates when the correlations in the tasks outside work arise from test-taking abilities (or other factors common across

We consider potential instruments from the exogenous factors that influence the frequency and types of tasks at work but are not directly related to an individual worker's cognitive skills. Potentially valid instruments are derived from available information on the demand side, e.g., the job requirements on tasks, and some exogenous changes in the work place (e.g. the number of employees change).

Table 9 lists our instrumental variables and reports their summary statistics. Specifically, the required education to get your current job provides information on the employers' demand on tasks at work. In PIAAC, workers are asked to report the usual education qualifications if applying today, someone would need to get for the type of their current job. In our sample 58% of employers require the applicants to have a college degree or above.

The employers design the job tasks and set the job requirements, generally applicable to all employees in the same occupation; it should be not directly correlated with an individual applicant's unobserved heterogeneity. Therefore, we construct two additional instruments on the importance of analytical/interactive task at occupation level based on data from the previous literature. More specifically, Acemoglu and Autor (2011) calculated the standardized score of composite measures of O*NET Work Activities and Work Context Importance scales at 1990 Census occupation level in USA. It represents the importance and requirements on analytical and interactive tasks in a specific occupation. We map the 337 1990 census occupations into 40 occupations in PIAAC, and average their standardized importance scores across the fitted occupations,

---

interactive and analytical tasks outside work) that are unrelated to ability. Its validity stands based on our arguments.

to get the average importance scales of analytical and interactive tasks at the PIAAC occupation level.

Another set of instruments are the changes of colleagues in the workplace and relative firm size. The size of work force is determined by the market demand on the products/services of the firm and local labor market conditions. Its changes lead to the redistribution of job tasks, but would not be directly related to a single employee's skill sets. More specifically, we use a dummy variable indicating the increase in the number of people working at the work place over the last 12 months; it reflects the necessary social interactions or coordination among coworkers, thus affecting the worker's interactive task frequencies at work. Also, the increase in colleagues will substantially influence the workload and task allocations in a small firm, so we include a dummy variable which equals 1 if the firm has at most 50 people as an additional instrument for US workers.

Table 9 – Instrumental Variables from Job Demand Information-PIAAC USA

Variable	Definition	Obs.	Mean	Std.	Min	Max
Required college education or above	1 if applying today, bachelor or above would be the usual qualifications, if any, that someone would need to get this type of your current job.	1811	0.58	0.49	0	1
Small firm size	1 if people work for your employer at the place where you work is 50 or below.	1811	0.41	0.49	0	1
Increase in colleagues	1 if over the last 12 months, the number of people working at the place where you work increased.	1811	0.26	0.44	0	1
Importance of analytical task at occupation level	the average standardized importance scale of analytical tasks at occupation level	1811	0.45	0.79	-1.69	1.69
Importance of interactive task at occupation level	the average standardized importance scale of interactive tasks at occupation level	1811	0.38	0.87	-1.14	2.40

The IV estimation results are reported in Table 10.

Table 10 – Instrumental Variable Approaches with All Job Tasks-PIAAC USA

Dependent variable: Cognitive skills	Instrumental Variables Approach		Multiple Indicator & Instrumental Variable Approach	
Complex task at work	2.139**	1.969**	2.127***	2.051**
	(0.897)	(0.850)	(0.764)	(0.884)
Interactive task at work	-0.0369	-0.0580	-0.0360	-0.0363
	(0.0948)	(0.0928)	(0.0806)	(0.0959)
Analytical task at work	0.0217	0.0432	0.0383	0.0189
	(0.193)	(0.189)	(0.191)	(0.197)
Experience	0.0307**	0.0297**	0.0313**	0.0304**
	(0.0130)	(0.0124)	(0.0133)	(0.0129)
Experience squared/100	-0.0382	-0.0354	-0.0407	-0.0375
	(0.0259)	(0.0249)	(0.0279)	(0.0257)
High school	0.277	0.278	0.278	0.244
	(0.199)	(0.192)	(0.197)	(0.193)
College	0.653***	0.647***	0.662***	0.584***
	(0.206)	(0.198)	(0.204)	(0.200)
Master or above	0.943***	0.933***	0.970***	0.850***
	(0.228)	(0.228)	(0.251)	(0.232)
Female	-0.175***	-0.196***	-0.159*	-0.186***
	(0.0646)	(0.0635)	(0.0876)	(0.0659)
Mother with tertiary education	0.141**	0.145**	0.139**	0.143**
	(0.0654)	(0.0629)	(0.0658)	(0.0651)
Father with tertiary education	0.238***	0.220***	0.245***	0.233***
	(0.0679)	(0.0650)	(0.0650)	(0.0670)
_cons	-2.434***	-2.435***	-2.360***	-2.657***
	(0.387)	(0.419)	(0.493)	(0.429)
Age dummies+ Industry dummies	Yes	Yes	Yes	Yes
Interactive task outside work		0.0474***	-0.0244	
		(0.0122)	(0.0751)	
Analytical task outside work		-0.0360		0.0999**
		(0.0372)		(0.0484)
N	1811	1811	1811	1811
Endogeneity test: Chi-squared test & p-value	69.37	65.20	65.61	106.4
	(0.000)	(0.000)	(0.000)	(0.000)
Overidentification test of instruments: Chi-squared test & p-value	1.90	2.09	1.81	2.42
	(0.388)	(0.351)	(0.404)	(0.298)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The general measure of job task complexity has a positive and significant impact on cognitive skills with a much enlarged magnitude. The effect of the analytical tasks at work remains positive but turns to be insignificant. The results are consistent with our previous results but will suffer from the finite sample bias.

The first stage results in Table 11 show that required education to apply for the current job are positively correlated with all the task complexity measures.

Table 11 – First-Stage Regressions of Instrumental Variable Approach with All Job Tasks–PIAAC USA

Dependent variable:	Complex task at work	Interactive task at work	Analytical task at work
Required college education or above	0.119***	0.099**	0.183***
	(3.60)	(3.19)	(5.72)
Small firm size	0.022	0.021	0.076***
	(0.97)	(1.00)	(3.44)
Increase in colleagues	0.045*	0.055**	0.063**
	(2.05)	(2.59)	(2.82)
Occupational analytical task importance	0.218***	0.128***	0.184***
	(6.70)	(3.93)	(5.36)
Occupational interactive task importance	-0.016	0.290***	0.110***
	(-0.67)	(10.96)	(3.89)
	1811	1811	1811

Standardized beta coefficients; *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As expected, the increase in colleagues will lead to an increase in interactive tasks at work; also, occupational importance scales in analytical and interactive tasks at work have a strong predictive power in the individual involvements in analytical and interactive tasks at work. We checked the redundancy of excluded instruments and did the over-identification tests. The instruments are both individually and jointly closely related to the complex tasks at work. They passed the overidentification test at 30-40% significance level.[19] Moreover, the exogeneity of tasks at work are rejected.

Although the IV estimation presumably produces consistent results, the requirements for the IVs are quite strong and it's hard to find valid instruments in practice. Furthermore, when we use the MI approach to address the omitted ability bias, we assume the remaining residual from the included indicator is uncorrelated with all the tasks at work. However, the remaining residual e.g., r_1 from interactive task outside work may be still related to interactive task at work, or even all the job task measures.

Based on the previous analysis, we did a more careful estimation. We address the omitted variable bias using tasks outside work as indicators, and simultaneously choose from our previous instrument variables from the job demand side to deal with the additional endogeneity from tasks at work. Compared to the MI approach, we use additional IVs to address remaining residual from interactive task outside work related to tasks at work. Our new estimates are reported in Table 24, column 3 and 4. The results of a combination of MI and IV are quite comparable to the MI results.

[19] The test on redundancy of excluded instruments uses a formulation based on testing the rank of the matrix cross-product between the endogenous regressors and the possibly-redundant instruments after both have all other instruments partialled-out. The test statistic is an LM test and numerically equivalent to a regression-based LM test. The over-identification tests reported Hansen's J statistic, it allows observations to be correlated within groups. For the endogeneity test, the test statistics is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous, it's robust to various violations of conditional homoscedasticity. We use robust standard errors; the above test statistics are all robust.

2.7 Conclusions

Work tasks have been more complex in the 21st century. It has raised important questions regarding the skills of the future in the fast-developing society. Cognitive skills are considered the fundamental skills to achieve success at work and in life. Our study do a detailed investigation of the research question: will workers be able to improve their cognitive skills through performing job tasks? It shed some new light on the development of cognitive skills in adulthood.

Our estimates show workers can benefit from on-the-job learning through solving complex tasks at work. More specifically, solving complex problems for at least once a month accounts for a 3-4th percentile increase in cognitive skills. The additional effect associated with complex analytical tasks relative to holding a general complex job is a 2th percentile increase in the skill distribution, while interactive tasks at work do not have a significant effect on cognitive skills.

However, comparatively those effects of on-the-job learning through tasks are also much smaller than those from early investments. The contribution of different sources of investments on cognitive skills follows a decreasing trend with their timing, and this is consistent with Heckman and Kautz (2013)'s analysis that cognitive skills are more malleable in early investments and much harder to accumulate in adulthood.

2.8 Appendix A: Combination of Multiple Indicator & Instrumental Variable Approach

The estimates in Table 10 are based on the estimator in combination of multiple indicator approach and instrumental variable approach. The estimation model is:

$$CS = \beta_{11} w_C + \beta_{12} w_A + \beta_{13} w_I + \lambda H\kappa + \beta_4 ex_t + \delta a_t + q + u$$

where we set w_C for general job task complexity, w_A for analytical task at work, and w_I for interactive task at work. H includes other variables that influence the quality of human capital at the labor market entry, such as the highest education completed, gender. q is unobserved heterogeneity. u is idiosyncratic.

If we have two indicators interactive task outside work nw_I and analytical task outside work nw_A for q, we first use multiple indicator approach to correct for the unobserved heterogeneity. Assume the indicators have a function form: $nw_I = \gamma_0 + \gamma_1 q + a_I, nw_A = \rho_0 + \rho_1 q + a_A$. After replacing q with nw_I, for example, $q = \frac{1}{\gamma_1}(nw_I - \gamma_0 - a_I)$, we would have the new model as follows:

$$CS_t = \beta_{11} w_C + \beta_{12} w_A + \beta_{13} w_I + \lambda H\kappa + \beta_4 ex_t + \delta a - \frac{\gamma_0}{\gamma_1} + \frac{1}{\gamma_1} nw_I - \frac{1}{\gamma_1} a_I + u .$$

Under the assumptions $Cov(a_I, a_A) = 0$, $Cov(a_I, q) = 0$, $Cov(a_A, q) = 0$, i.e., nw_I and nw_A are not correlated after netting out q, we could use nw_A as instrument for nw_I because it satisfies $Cov(nw_A, -\frac{1}{\gamma_1} a_I + u) = 0$ and $Cov(nw_I, nw_A) \neq 0$.

a_I represents the residual of interactive task outside work netting out q. Here another source of endogeneity for consideration is $Cov(w_I, a_I) \neq 0$. Therefore, we use z_I as instrument for w_I if z_I satisfies $Cov(w_I, z_I) \neq 0, Cov(z_I, u) = 0, Cov(z_I, a_I) = 0.$

For interactive task measures at work we choose the change in colleagues, the O*NET occupational interactive task importance scale as instruments.

In the model a_I would not be correlated to w_A because of the same MI orthogonality assumption for interactive tasks and analytical tasks outside work after netting out the ability. Furthermore, w_c represent the general task complexity at work. It should be exogenous after we take out the ability using MI approach.

In summary, the model

$CS_t = \beta\delta_{11}w_C + \beta_{12}w_A + \beta_{13}w_I + \lambda H\kappa + \beta_4 ex_t + \delta a - \frac{\gamma_0}{\gamma_1} + \frac{1}{\gamma_1}nw_I - \frac{1}{\gamma_1}a_I + u$ could be consistently estimated with 2SLS with the instruments $(w_C, w_A, z_I, H, ex, a, 1, nw_A)$.

Similar analysis applies to the case when we use analytical task outside work nw_A as included indicator in the model, then the analytical task at work would be endogenous instead. The valid instruments include the required education to get the current job, O*NET occupational analytical task importance.

CHAPTER 3 JOB TASK COMPLEXITY AND PROBLEM-SOLVING SKILLS

3.1 Introduction

Based on Lucas (2009), the industrial revolution was marked by the emergence of a class of educated people who exchange ideas, solve work-related problems and/or generate new knowledge. Workers solve work-related problems through dealing with a bundle of job tasks. However, job tasks have changed dramatically during the past 60 years. For example, Autor, Levy and Murnane (2003) found computerization increased non-routine problem-solving tasks and complex communication tasks from 1960 to 1998 in US. Similarly, Spitz-Oener (2006) suggests that occupations involve greater complexity over time, and have experienced a shift toward analytical and interactive activities and away from cognitive and manual routine tasks.

The rise of nonroutine job tasks are expected to explain the dynamics in the worker composition: firstly, it raised demands on high skilled workers who are more capable to solve problems without implicit methods; secondly, it provides a possible channel for workers to accumulate non-routine skills. In this study, we particularly investigate how job tasks help improve a worker's problem-solving skills.

However, there have been two problems in studying the effect of job tasks on a worker's skills. One is the lack of a good measure of job tasks, because on-the-job learning is usually measured using years of experience. This approach ignored the heterogeneity in on-the-job learning as workers with the same years of experience, even within the same occupation, may perform very different job tasks. Another one is the lack of measurement of a worker's skills.

This study uses tasks at work at individual level to investigate in more details about on-the-job learning. We use two survey data sets in Germany. The analysis primarily uses data from the Programme for the International Assessment of Adult Competencies (PIAAC) data (2012) organized by the OECD. The survey for the first time contains both a direct assessment of problem-solving skills (PS), and information on tasks performed at workplace at individual level. In addition to PIAAC, we also use a new survey data (2013) from the "LLLight'in'Europe" project (LLL), funded by the European Union. It contains information on higher level of problem-solving skill of an individual, i.e., complex problem-solving skills (CPS). The two datasets complement each other and allow this study to not only investigate how job tasks affect one's general problem-solving skills but also on complex problem-solving skills.

This study contributes to the literature on the relationship between job tasks and skills. Most studies in the task related literature, e.g., Autor, Levy and Murnane (2003); Poletaev and Robinson (2008), Gathmann and Schönberg (2010); Autor and Handel (2013), implicitly consider job tasks as measures for unobserved worker skills. They implicitly assume that skills could be measured by observed job tasks. However, the direct relationship between individual tasks performed and the level of one's human capital remains to be not fully understood. Yamaguchi (2012) suggests that observed task complexity can only be interpreted as a noisy signal of unobserved skills, because those performing similar tasks may have different skills.

Our study makes a clear distinction between job tasks and skills, and investigates how job tasks contribute to skill improvement. It is similar to the idea proposed by Yamaguchi (2012). It lays out a structural dynamic model of occupation choice and skill formation, and represents the technology of skill formation by a function of task complexity at occupational level. Their estimates suggest that cognitive and motor skills grow faster when working in an occupation characterized by more complex job tasks.

Moreover, because of the limited data on tasks at work, the majority of previous research including Yamaguchi (2012) constructed the job task measures by matching the aggregate occupation level task characteristics to micro data based on the occupational code. The potential problem is that the aggregate level task measures are not a perfect measure the actual tasks performed at work (see Gibbons and Waldman (2004), Spitz-Oener (2006), and Autor and Handel (2013)). For example, Autor and Handel (2013) found that individual job tasks vary significantly within and between occupations. Therefore, our study uses job tasks at the individual level, which provides a more accurate measure of tasks performed at work. More specifically, we construct three measures of job complexity: a general job complexity measure and two specific measures on interactive tasks and analytical tasks.

In summary, our research has a clear distinction between job tasks and skills; it complements the current series of literature on tasks with an investigation on the relationship between job tasks and skills. We focus our analysis on problem-solving skills, which have not had sufficient assessments available for working adults; the two datasets for Germany we use narrow the gap and measure different levels of problem-solving skills. Differing from most of the previous research which uses overall experience and occupation types to capture on-job learning, we use individual level tasks performed as a more accurate measure of on-job learning.

The difficulty in identifying the causal effect of job tasks on skills is due to the selection into job tasks by workers themselves. Therefore, to address the selection problem due to unobserved individual heterogeneity, various econometric techniques are applied to estimate the causal learning effect.

Our results show that the complexity improves a worker's problem-solving skills. More specifically, the general task complexity plays an important role in improving an individual's problem-solving skill. Additionally, analytical tasks contribute the accumulation of problem-solving skills, while interactive tasks do not have a significant effect. Moreover, task complexity can also contribute to complex problem-solving skills but with a much smaller magnitude of effects, which implies that CPS are more difficult to accumulate.

3.2 Problem-solving Skill Accumulation with Job Tasks

The typical model of skill formation postulates that skills at current period depend on skills at previous period, invariant ability, and investments at current period. The skill accumulation is a dynamic process with a combination of inherited skills and acquired part with lifetime investments. (Ben-Porath 1967, Cunha and Heckman 2007, Cunha, Heckman and Schennach 2010, Yamaguchi 2012). Therefore, the skill stock for working adults could be written as a function of the initial skill stock, skill accumulation at each job, and skill depreciation with age as below:

$$h_t = F(h_0, I_1, I_2, ...I_t, a_t), t = 1, 2, ..., n \qquad (1)$$

where t represents the number of jobs, h_0 is the initial skill endowment at the labor market entry. a_t means the cumulative depreciation up to age at job t for human skills (Pfeiffer and Reuß 2008). I_t is investment in human capital skills at job t.

In this study, the investment is defined by on-the-job learning. We conceive of a job as an indivisible bundle of task demands, all of which are performed simultaneously by each worker in the job. Jobs differ in which tasks they require and in the relative importance of each task for production. The jobs could be ranked in the order of task complexity.

According to Gathmann and Schönberg (2010), individuals become more productive in each task through passive learning-by-doing with experience, and the amount of learning in each task depends on how important the task is in that job. Therefore, here we specify that on-the-job learning is not only measured through overall years of job experience but also the job tasks performed:

$$I_t = \{ew_t, w_t\} \quad (2)$$

where ew_t is the job tenure at job t, and w_t means a range of tasks performed at job t, which reflects the quality of learning by doing at work.

Under the simplying assumptions on the function form, consider the regression analog of the true technology (1), namely:

$$h_t = \lambda h_0 + f(I_1, I_2, \ldots I_t)\beta + \delta a_t \text{ , (3)}$$

where $f(I_1, I_2, \ldots I_t) = f(w_1, w_2, ..w_t; ew_1, ew_2, \ldots, ew_t)$. In other words, skill accumulation at work depends on the tasks performed in a job and the tenure of the job.

When data on job task are not available for previous jobs, the contemporaneous specification relates an achievement test score measure solely to contemporaneous measures on work task inputs. The following assumption on the production technology and on the input decision rules would justify its application: current input measures capture the entire history of inputs. In reality, tasks performed in the current job are closely correlated with the tasks performed in the previous jobs. An individual generally starts with a job at which the tasks are relatively simple, and then the complexity of job tasks may change within the job tenure or when he/she moves to another job. However, the mental and physical costs of the adjustment are high when entering into a job that is very different from the past occupations held. This argument is supported by Gathman and Scho¨nberg's (2010) longitudinal study, which employs occupation-level measures of job tasks in Germany and finds that workers move mostly to new occupations that have task requirements that are similar to those of their previous occupations when they change jobs.

Therefore, we assume that tasks performed at the current job could be represented by a function of tasks performed in previous jobs and the corresponding job tenures, and get the following function:

$$w_t = g(w_1, w_2, ...w_{t-1}; ew_1, ew_2, ..., ew_{t-1}, ew_t)\,. \quad (4)$$

Then we can express $w_1, w_2, ...w_{t-1}$ through $g^{-1}(w_t; ew_1, ew_2, ..., ew_{t-1}, ew_t)$ as below:

$$f(I_1, I_2, ...I_t) = f(g^{-1}(w_t), w_t; ew_1, ew_2, ..., ew_t)\,. \quad (5)$$

Replacing the task information for previous jobs with the information on the tenure of previous jobs, we can use the following model:

$$h_t = \lambda h_0 + f_h(w_t; ew_1, ew_2, ..., ew_t)\beta + \delta a_t\,. \qquad (6)$$

Furthermore, when the specific job tenure at each previous job is missing we use the number of jobs worked t and the cumulative work experience ex_t to proxy the tenure for each job $ew_1, ew_2, ..., ew_t$. We also consider the case that the current job tenure reflects the quantity of learning at the current job and affect the skill accumulation through current job tasks, and then get:

$$h_t = \lambda h_0 + f_h(w_t, ew_t; t, ex_t)\beta + \delta a_t\,. \qquad (7)$$

Thus, skill accumulation can be represented by the tasks of current job, the tenure of the current job, the total number of jobs, and the overall length of work experience. Based on the previous analysis, we then obtain the model as below:

$$h_t = \lambda h_0 + w_t\beta_1 + (ew_t \cdot w_t)\beta_2 + \beta_3 t + \beta_4 ex_t + \delta a_t \qquad (8)$$

where in this study h represents problem-solving skills PS . Our research hypothesis is that workers accumulate problem-solving skills faster when they are more frequently involved in solving complex tasks at work, because they have more learning-by-doing opportunities through dealing with job tasks and can acquire more skills in the problem-solving process. The effect of learning by doing on-the-job is expected to be stronger for problem-solving skills compared to traditional cognitive skills such as literacy and numeracy skills.

The view of learning-by-doing through tasks at work is supported by research in psychology, Davidson and Sternberg (2003) summarized earlier psychology research on problem-solving processes. More specifically, Individuals are expected to go through all or part of these metal processes to cope with different types of tasks at work: problem solvers need to identify the problem, develop a solution strategy, organize his or her knowledge about the problem, allocate mental and physical resources for solving the problem, monitor his or her progress toward the goal, and evaluate the solution for accuracy.[20] Take the computer technician as an example: when they troubleshoot a variety of computer issues, they need to first explore and figure out the potential computer problem, and then come up with a technical solution. If it doesn't work, they need to recheck and make the computer system run in the end. Such a kind of experience would help workers understand the essence of problem solving, and gain efficiency to

[20] Psychologists analyzed the influencing factors of problem-solving skills in psychology by the elements that contribute to the metacognitive processes involved in recognizing, defining, and representing problems. Psychological research on problem-solving has identified knowledge, cognitive processes and strategies, individual differences in ability and dispositions, as well as external factors such as social context that will affect problem-solving performance.

tackle a difficult problem or task in the future. The literature in organizational behavior and management psychology also identified the effects of repetitive tasks at work on workers' performance. For example, Häusser, Schulz - Hardt et al. (2014) show experimental evidence that high task repetitiveness increases work performance.

In this specification, w_t represents a $1 \times n$ vector of different tasks at work, [w_{1t}, $w_{2t} \ldots, w_{nt}$]. The marginal effects of tasks at work are represented by β_1. β_2 captures the dynamic learning process in the current job. Additionally, assume that the initial skill endowment at the labor market entry h_0 is composed of observed and unobserved components:

$$h_0 = H\kappa + q \qquad (9)$$

where H are the observed individual characteristics, and q are the unobserved individual skill endowments (e.g., ability, motivation, preference, etc.). Therefore, we have the empirical model as follows:

$$h_t = \lambda H\kappa + w_t\beta_1 + (ew_t \cdot w_t)\beta_2 + \beta_3 t + \beta_4 ex_t + \delta a_t + q + u\,, \quad (10)$$

where H includes other variables that influence the quality of human capital at the labor market entry, such as the highest education completed, gender; q represents the unobserved component of initial skills, e.g., ability, motivation, preference, etc.; u is the idiosyncratic error term.

3.3 PIAAC Data and Sample Descriptive Statistics

We use the data from the Programme for the International Assessment of Adult Competencies (PIAAC) for Germany. Germany is well known for utilization of both the general education system and the apprenticeship system (Freeman and Schettkat 2001). After completion of the apprenticeship training, employers also provide continuous on-the-job training. The formal training and informal training on-the-job by colleagues or through learning-by-doing are considered to play a large role in workers' skills development there (Pischke 2001). Here our study focuses on testing whether learning-by-doing will contribute to the skill accumulation of workers in Germany.

Our sample includes full-time employed workers whose age ranges from 16 to 65. The industries generally belong to manufacturing, construction, service and trade industries.[21] The sample statistics for the PIAAC German sample are reported in Table 12.

[21] The PIAAC data has very detailed industry classifications. Because it is unlikely that workers' problem-solving skills vary systematically across narrowly defined industries, we combine them into broader categories as manufacture/construction and service/trade to save degrees of freedom, and the broad industry dummies are included in the estimation to capture industry-specific fixed effects on workers' problem-solving skills. A more detailed classification of industry fixed effects does not change the results in any significant way. We excluded agriculture and military industries because they have a different mechanism of learning through work activities.

Table 12 – Variable Definition and Summary Statistics-PIAAC Germany

Variables	Definitions	Obs	Mean	Std. Dev.	Min	Max
Experience	Total number of years with paid work	1598	19.35	11.98	0	47
Years-current employer	Years worked for the current employer	1596	11.41	10.07	1.5	45
Middle school or below	1 if middle school education or below	1598	0.043	0.202	0	1
High school	1 if high school diploma	1598	0.420	0.494	0	1
College	1 if college degree	1598	0.273	0.446	0	1
Master or above	1 if master degree or above	1598	0.265	0.441	0	1
Female	1 if female	1598	0.339	0.473	0	1
Age	Age	1598	40.62	11.55	17	62
Mother with high school or above	1 if mother's highest education is high school or above	1598	0.753	0.431	0	1
Father with tertiary education	1 if father's highest education is college or above	1598	0.342	0.474	0	1
Manufacturing industry	1 if manufacturing, electricity supply, water supply, construction, etc.	1598	0.38	0.486	0	1
Service, Trade industry	1 if wholesale, retail trade, accommodation, financial and insurance, education, etc.	1598	0.62	0.486	0	1

Source: the International Assessment of Adult Competencies (PIAAC), 2012, Germany.

Education is measured by the highest education qualification reported by workers.[22] In Germany, students attend primary school for 4 years, and then are placed into 1 of 3 tracks for secondary education depending on their overall academic performance, i.e., basic track (Hauptschule), middle track (Realschule), and academic track (Gymnasium). The first two prepare students for vocational training, including vocational school education and on-the-job training. To attend higher education, students need to obtain a degree from the 3rd track, i.e., the academic track (Lohmar and Eckhardt 2014, Riphahn and Zibrowius 2016). Therefore, German's education system is more job-oriented at the early stage of the education path and German students are more likely to enter the job

[22] The PIAAC follows the International Standard Classification of Education (ISCED) 1997.

market without a college degree. Consistent in our sample (Table 1), 27.3% workers completed college and 42% completed only high school in Germany.

As for work history, the average years of experience is 19.4 for Germany.[23] Workers in Germany stay in their jobs for a long time; for example, their tenure in the current job on average is 11.4 years.[24] It's consistent with the features of German labor market, which is often viewed as a heavily regulated labor market, with firing restrictions, centralized wage-setting institutions, and generous unemployment insurance coverage (Botero, Djankov et al. 2004, Schönberg 2007). At the same time it raises some interesting questions on the learning dynamics on the job for German workers. In particular, will workers improve problem-solving skills more effectively when staying in a fixed job for a longer period of time? We will explore this question in the regression analysis below.

3.3.1 General Problem-solving Skill Measure

The PIAAC data provides a new measure of skills of adults, namely, problem-solving skills in technology-rich environment (abbreviated as PS below).[25] The PIAAC

---

[23] The PIAAC asks workers to report how many years they have had paid work, which includes years with 6 months or more spent in either full-time or part-time work.

[24] The current age and the age at the time the worker started working for the current employer are available in the data; we calculate the tenure with the current employer based on their difference.

[25] Their tasks for skill measurement include deciding on one among several possible strategies; making use of adequate functionalities in a context-sensitive manner; interpreting ill-structured texts; using online forms. More specifically, there are 14 problem-solving items included in the PIAAC assessment; and they have three types of scenarios: a. Short scenarios where the tasks are most direct and least complex, for example, individuals are asked to evaluate the choices and select one that meets some specified criteria from a simulated page of hits from an internet search; b. 10-minute scenarios that involve multiple steps, and sometimes multiple technology environments: workers may be required to locate an email, open and look at an attachment to create a brief information table for a specific purpose. c. 15-minute scenarios that involve recursive and exploratory activities in nature. One sample is test takers do a search in a simulated web environment, integrate and evaluate information across different sites, then use information to generate a summary to be shared as part of a community presentation.

problem-solving survey is designed to test the abilities to solve problems for personal, work, and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer networks.[26] Although PS tasks are related to the use of information and communication technologies (ICT), the test only needs basic ICT skills. As noted in the OECD website, PS is "not a measurement of computer literacy, but rather of the cognitive skills required in the information age."[27]

The test for skills ranges 0-500 points in the PIAAC survey, with higher points representing higher level of skills.[28] In the regressions, we transform it into z-values for analysis purpose. As is shown in Table 13, the workers have an average score of 290.0 points for PS. The scores increase with education. For example, the average score of PS is 257.0 points for those with a below high school education but 296.3 points for those with a college degree.

In Table 13 we list the PS scores based on years of job experience. Generally speaking, PS grows first and declines with job experience. There is a mild improvement in PS sores with work experience, e.g., the average score of German workers with 4-7 years' experience is 9 points higher than the average score with 0-3 years' experience, and then declines slightly with more experience.

[26] In this paper, we use "ability" and "skills" interchangeably. The ability/skill measure here is a combination of unchanged ability and learned skills, so the measure will not change with time if it's designed to measure an unchanged ability, and mostly reflects the learned skills if it does change.
[27] More specifically, according to OECD (2012), an assessment of problem-solving capacities focuses on situations where test takers cannot immediately reach their goal based on a routine, mechanical sets of actions, and thus the focus is on tasks that require test takers to actively construct a solution based on the resources available in the assessment environment. OECD website:http://www.oecd.org/skills/ESonline-assessment/skillsassessed/.
[28] In this paper, we use the average of 10 plausible values of the PIAAC skill scores in each domain.

Table 13 – The Dynamic Trend of Problem-solving Skills with Experience-PIAAC Germany

Variables	Obs	Mean	Std. Dev.	Min	Max
Score for problem-solving skills(PS)	1598	290.0	38.9	145.5	392.8
Total years of experience	Obs	PS			
0-3	155	295.0			
4-7	191	304.5			
8-11	157	298.9			

One reason is on the job learning; and the other reason is the accompanying effect of aging that may reduce an individual's PS as years of job experience increases. However, years of job experience is a general measure of on-the-job learning, because tasks performed vary dramatically across jobs.

3.3.2 Job Task Complexity Measures

Next, to analyze how task-specific experience affects problem-solving skills, we look at tasks that a worker performs in his/her job and introduce our measure of job task complexity. The descriptive statistics of the job task measures are reported in Table 14. The statistics show that overall 68.9% of German workers deal with complex tasks at least once a month. Additionally, German workers reported that they are involved in 47.7(41.0) % of representative interactive (analytical) tasks at least once a week. The correlations between the general task complexity and two specific task complexity measures are 0.28-0.38.

Table 14 – Tasks at Work-PIAAC Germany

Variables	Definitions	Obs	Mean	Std. Dev.	Min	Max
Complex task at work	1 if confronted with more complex problems that take at least 30 minutes to think of a good solution at least once a month at work	1598	0.689	0.463	0	1
Interactive task at work	Share of tasks that performed at least once a week among 13 interactive tasks at work	1598	0.477	0.201	0	1
Analytical task at work	Share of tasks performed at least once a week among 18 analytical tasks at work	1598	0.410	0.220	0	1

3.4 The Effect of Job Task Complexity on Problem-solving Skills

We have estimated a variety of empirical models to answer the question: can workers improve their problem-solving skills through job related tasks? Our initial approach is to augment a standard cross-sectional skill formation model with job complexity measures. Then we go further to explore whether there is a substantial heterogeneity in the effects of different job tasks on problem-solving skills. Given the available information on the cross-sectional data, we try to identify learning dynamics and estimate several different model specifications.

Our benchmark OLS results are reported in Table 15. In the first column, we include the general complexity of tasks at work. Considering the general task complexity measure would capture all the effects of interactive and analytical tasks at work, we tried the model specification with only the interactive and analytical tasks at work in the second column. The third column includes all these job task measures. Under the assumption that the skill accumulation with experience will depreciate with age, we use experience, and experience interacted with age, as a parsimonious approach. We don't include the number of jobs held in the estimation for the PIAAC dataset because it doesn't have the information.

Table 15 – Baseline Results of Problem-solving Skills & Tasks at Work-PIAAC Germany

Dependent variable:	PS	PS	PS
Complex task at work	0.257***		0.130**
	(0.0498)		(0.0509)
Interactive task at work		0.00878	0.00190
		(0.0123)	(0.0125)
Analytical task at work		0.0967***	0.0918***
		(0.0115)	(0.0116)
Experience	0.0166*	0.0119	0.0110
	(0.00928)	(0.00915)	(0.00915)
Experience*Age	-0.000669***	-0.000600***	-0.000584***
	(0.000153)	(0.000150)	(0.000150)
High school	0.505***	0.470***	0.460***
	(0.120)	(0.117)	(0.117)
College	0.967***	0.871***	0.844***
	(0.125)	(0.122)	(0.123)
Master or above	1.252***	1.132***	1.097***
	(0.124)	(0.123)	(0.124)
Female	-0.126**	-0.128**	-0.125**
	(0.0459)	(0.0447)	(0.0447)
Mother with high school or above	0.282***	0.249***	0.247***
	(0.0532)	(0.0519)	(0.0516)
Father with tertiary education	0.116**	0.100**	0.100**
	(0.0452)	(0.0447)	(0.0447)
_cons	-0.877***	-0.991***	-1.006***
	(0.130)	(0.127)	(0.127)
Industry dummies	Yes	Yes	Yes
N	1598	1598	1598
adj. R^2	0.309	0.339	0.341

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As another important channel of human capital accumulation, the highest education degree obtained by the workers was included in our estimation. Besides that, we use parents' education as a proxy for unobserved initial skill endowments q. It produces consistent estimates assuming that parents' education is a perfect proxy, i.e., redundant to the model if q is included, and is to purge the correlation between human capital investments and unobserved individual skills.

The result in the first column shows that the job task complexity has a positive and significant effect on problem-solving skills. It indicates that when individuals are involved in complex tasks for at least once a month at work, their problem-solving skills are expected to be 0.26 standard deviation higher, i.e., workers at the 50th percentile move up to the 60th percentile in PS.

The results show that PS grows with experience and follows a concave growth path, presumably because of the ageing effect. A 10 year's increase in work experience increases problem-solving skills by 0.17 standard deviation (an increase by a 6.8th percentile from the mean), and the depreciation with age dominates the growth with experience from 25 years old.

The other estimates in the model are as expected in sign and significance. Our results show that workers with higher education own higher skills. In particular for problem-solving skills, workers with a high school degree, college degree, and master degree or above have 0.51, 0.97, 1.25 standard deviation higher PS compared to those with a junior school degree or below. Parents' education helps capture the inherited endowments and early childhood family education. Our results show that a German worker whose father has a college degree or above has a 0.12 points' higher PS while mother's education leads to a 0.25 points increase.

In comparison, the effect of the general complexity measure becomes much smaller but remains highly significant with interactive and analytical tasks included in the third column. In this case, it helps reflect other tasks that are not captured by interactive and analytical tasks. Accordingly, with all task measures included in Column 3, the coefficients on the specific tasks should be interpreted as indicating the additional effect associated with a specific task relative to a general complex job. The results show that the general measure of job complexity still has the highest effect. It's followed by analytical tasks, which shows that if workers deal with 10% more analytical tasks among the 18 tasks for at least once a month at work, their problem-solving skills will increase by an additional 0.09 standard deviation (an additional increase by a 3.6th percentile). However, the interactive task has a statistically insignificant effect on PS.

We do a further investigation on the existence of dynamic on-the-job learning with task-specific investments in Table 16 for PS. We are interested to know how the task-specific job tenure will affect the return to tasks. Therefore, we add the interaction terms between the current job tenure and the current job task characteristics. Column 1 adds solely the interaction term between a general complex task measure and current job tenure, and column 2 adds solely the interaction term between the analytical task at work and current job tenure. The results in Table 16 provide supporting evidence for the existence of dynamic learning by doing at work. The results in column 1 show that 10 years' intensive work in complex tasks at the current job leads to an additional significant 0.07 standard deviation (a 2.8th percentile) higher PS, however, the effect of general task complexity turns insignificant. The PS of workers with 10 years' experience in analytical tasks at their current job increases by 0.02 standard deviations.

When both interaction terms are added for interactive and analytical tasks at work, the results of tasks at work become less significant or insignificant, probably because of a high degree of collinearity (0.60-0.70) between tasks at work and their interaction terms with current job tenure. Also, the model with interaction terms doesn't add much value in terms of the model of fit. Therefore, in the following estimations we focus in our analysis on the more parsimonious model without interaction terms.

Table 16 – Learning Dynamics with Job Tasks-PIAAC Germany

Dependent variable:	PS	PS
Complex task at work	0.0491	0.130^{**}
	(0.0618)	(0.0511)
Interactive task at work	0.000668	0.0000130
	(0.0125)	(0.0125)
Analytical task at work	0.0934^{***}	0.0767^{***}
	(0.0116)	(0.0131)
Complex task at work*current job experience	0.00703^{**}	
	(0.00294)	
Analytical task at work*current job experience		0.00147^{**}
		(0.000540)
Experience	0.0112	0.0111
	(0.00921)	(0.00921)
Experience*Age	-0.000621^{***}	-0.000629^{***}
	(0.000150)	(0.000151)
# of different firms worked for in the past 5 years	0.0256	0.0266
	(0.0197)	(0.0198)
High school	0.472^{***}	0.471^{***}
	(0.116)	(0.116)
College	0.854^{***}	0.858^{***}
	(0.122)	(0.122)
Master or above	1.106^{***}	1.109^{***}
	(0.123)	(0.123)
Female	-0.122^{**}	-0.121^{**}
	(0.0446)	(0.0446)
Mother with high school or above	0.247^{***}	0.246^{***}
	(0.0515)	(0.0514)
Father with tertiary education	0.108^{**}	0.107^{**}
	(0.0449)	(0.0449)
_cons	-1.034^{***}	-1.020^{***}
	(0.134)	(0.134)
Industry dummies	Yes	Yes
N	1596	1596
adj. R^2	0.342	0.342

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5 Can the Effects of Task Complexity be explained by Unobserved Heterogeneity?

The concern with the previous estimates is the correlation between unobserved heterogeneity q and task complexity cannot be fully captured by the parents' education. Then the effects of task complexity on PS would be biased due to omitted variables. For example, workers have their comparative advantage in different types of tasks. More skilled workers are more productive in complex tasks than low skilled workers. Therefore, working adults with higher ability, motivation, and preference for challenges are more likely to self-select into complex job tasks. In addition, employers may allocate job tasks based on some personal characteristics observable to employers but not econometricians. For example, employers allocate workers who are more outgoing to sales, and assign workers with a good appearance to service work.

3.5.1 Selection into Job Tasks

We first explore the potential existence of bias from selection into tasks with the job change information. It's possible that the empirical estimates on the dynamic learning with job tasks between workers who changed jobs and those who don't suffer different degree of endogeneity. The logic is for workers who haven't changed jobs, especially those who just started working, the selection would be less because when a worker starts his/her first job. They usually have incomplete information on their own capabilities and also the actual job characteristics, while at the same time employers cannot observe their true productivities and skills. However, for workers who changed jobs, there would be a higher degree of selection because workers with high ability and motivation will prefer to do more complex tasks at work, or employers have better information on their skills based on the realized productivities and hire them to cope with more challenging job tasks.

Therefore, we first estimate the baseline model using a subset of samples that never changed jobs. We first obtained the approximate tenure with the current employer based on the year the worker started working for the current employer in PIAAC, and compare it with the total number of work experience to determine whether he/she changed jobs. Also, in PIAAC workers are asked to report the number of different employers/institutions he/she worked for within the past 5 years. We restrict those workers to work for one employer/institution within the past 5 years.

The results in Table 17 indicate that workers who don't change jobs could accumulate their problem-solving skills by 0.07 standard deviation when they have a 10% increase in the share of 18 representative analytical tasks at work. The general job complexity measure and interactive tasks at work show no significant effect in the skill formation.

For those who changed jobs, we add some additional controls to capture the job change information. We add the tenure for the current job into the model because the number of years an employer worked for a particular employer shows the quantity of on-the-job learning with the task characteristics specific to the employer. We also controlled for the number of employers they worked for in the past 5 years as a partial control of the number of jobs held because the number of employers worked for could help capture different contents of learning at work.

Table 17 – Selection into Tasks & Job Change-PIAAC Germany

Dependent variable: PS	Current job experience=Total experience	Current job experience<Total experience
Complex task at work	0.137	0.125**
	(0.128)	(0.0560)
Interactive task at work	-0.0262	0.00338
	(0.0280)	(0.0139)
Analytical task at work	0.0688**	0.0970***
	(0.0279)	(0.0128)
Current job experience		0.00761**
		(0.00320)
Experience	0.0370	0.00737
	(0.0255)	(0.0106)
Experience*Age	-0.00104**	-0.000567***
	(0.000454)	(0.000167)
# of different firms worked for in the past 5 years		0.0354*
		(0.0218)
High school	0.527**	0.449***
	(0.260)	(0.133)
College	1.132***	0.804***
	(0.292)	(0.139)
Master or above	1.378***	1.051***
	(0.293)	(0.141)
Female	-0.279**	-0.0990**
	(0.103)	(0.0494)
Mother with high school or above	0.255**	0.247***
	(0.126)	(0.0565)
Father with tertiary education	0.130	0.104**
	(0.107)	(0.0496)
_cons	-0.918***	-1.113***
	(0.246)	(0.164)
Industry dummies	Yes	Yes
N	251	1345
adj. R^2	0.342	0.338

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show that the workers who changed jobs and have a complex current job will have a 0.125 standard deviation higher PS. The effect is statistically significant while it's insignificant for workers who never changed jobs. Also, the intensive problem-solving in analytical tasks at work will contribute to an additional 0.097 standard deviation higher PS. The effects are relatively larger than those for non-job changers. Furthermore, it seems with a ten years' increase in the tenure for the current job, the workers are expected to have 0.07 standard deviation increase in PS. The number of job changes in the past 5 years has a positive but insignificant effect on skill formation.

In comparison of the results between job changers and non-job changers, it implies that the selection issues will lead to a positive bias in the marginal effect of job task complexity on PS. Therefore, we will further investigate whether the effects of task complexity can be fully explained by unobserved heterogeneity with additional information on the unobserved heterogeneity.

3.5.2 Tasks outside Work and Unobserved Heterogeneity

In Table 18, we relax the assumption that parent's education is a perfect proxy for individual heterogeneity q, and add analytical and interactive tasks outside work as an additional proxy.

The PIAAC survey asks workers to report how often they deal with tasks outside work.[29] Following a similar procedure for tasks at work, we define an interactive task outside work and an analytical task outside work with a certain degree of complexity accordingly.[30] In particular, among those 17 analytical activities outside work, we define the complexity of analytical tasks with the share of tasks among 17 tasks that have a frequency of at least once a week. Similarly, we measure the complexity of interactive tasks with the share among the 4 interactive activities outside work. The details on

[29] The PIAAC questionnaire asks "in everyday life, how often do you…." and notes that it means tasks outside work if workers are currently working. The individuals are asked to report the frequency of activities outside work, excluding any part done for the job and including any part done as part of studies.

[30] We exclude some tasks if the responses are very similar for those tasks, e.g., more than 95% of individuals do not do it on a weekly basis.

representative tasks are listed in Table 7. Workers report that they deal with 65.3% of 4 interactive tasks at least once a week outside work. However, they only do 33.1% of 17 analytical tasks outside work. The correlation between interactive (analytical) tasks outside work and those tasks at work is 0.16 (0.34).

Those tasks outside work are not mandatory, and thus help capture additional unobserved heterogeneity. In particular, they reflect personal preferences, interests in specific tasks, ICT usage, personal motivation, or related learning outside work. For example, the measurement of the interactive tasks outside work is based on 4 tasks including online communications; email usage; reading letters, memos or emails; and writing letters, memos, or emails.[31] These tasks outside work are daily communications through emails and online chatting tools. They capture to a large extent the unobserved ability to use information and communication technologies, which may lead to a higher skill score in the PIAAC. They also help reflect workers' preference towards communication work tasks because they are not mandatory or required to do outside work. Similar arguments apply to analytical tasks outside work. The tasks outside work on reading financial statements, and reading professional journals, reflect individuals' financial and professional knowledge. We use a similar approach to Krueger (1993), who controls for whether workers use a computer at home and check whether the return to computer use at work is spurious.[32]

[31] We tried to use only the online communications and email usage to define the interactive tasks outside work because they are interactive tasks with ICT tools. The results show that the effect of interactive tasks outside work on problem-solving skills using 4 representative tasks is dominated by the effect of the measure defined with only two tasks because their effects' magnitude is quite similar. The representative tasks outside work are dominated by the interactive tasks with ICT tools.

[32] We also tried a more general specification assuming the interactive tasks outside work affect the impact of interactive tasks at work on production of problem-solving skills; and the same for analytical tasks. Thus we include interaction terms between measures for task at work and outside work. If the coefficient estimate for the interaction term is positive, it reflects the complementary effect between tasks outside work

Table 18 – Problem-solving Skills & Tasks at Work with Tasks outside Work as Proxy-PIAAC Germany

Dependent variable:	PS	PS	PS
Complex task at work	0.229^{***}		0.144^{**}
	(0.0485)		(0.0500)
Interactive task at work		-0.00337	-0.0111
		(0.0124)	(0.0124)
Analytical task at work		0.0863^{***}	0.0807^{***}
		(0.0119)	(0.0120)
Interactive task outside work	0.0724^{***}	0.0691^{***}	0.0697^{***}
	(0.00912)	(0.00899)	(0.00898)
Analytical task outside work	0.0310^{**}	0.00244	0.00324
	(0.0124)	(0.0133)	(0.0133)
Experience	0.0198^{**}	0.0169^{*}	0.0159^{*}
	(0.00890)	(0.00891)	(0.00890)
Experience*Age	-0.000638^{***}	-0.000602^{***}	-0.000583^{***}
	(0.000146)	(0.000145)	(0.000145)
High school	0.466^{***}	0.462^{***}	0.450^{***}
	(0.114)	(0.114)	(0.114)
College	0.885^{***}	0.849^{***}	0.819^{***}
	(0.120)	(0.120)	(0.121)
Master or above	1.169^{***}	1.120^{***}	1.081^{***}
	(0.120)	(0.121)	(0.122)
Female	-0.0895^{**}	-0.0982^{**}	-0.0941^{**}
	(0.0448)	(0.0440)	(0.0439)
Mother with high school or above	0.248^{***}	0.229^{***}	0.227^{***}
	(0.0518)	(0.0512)	(0.0509)
Father with tertiary education	0.108^{**}	0.0975^{**}	0.0974^{**}
	(0.0446)	(0.0442)	(0.0441)
_cons	-1.419^{***}	-1.415^{***}	-1.436^{***}
	(0.133)	(0.132)	(0.132)
Industry dummies	Yes	Yes	Yes
N	1598	1598	1598
adj. R^2	0.351	0.367	0.370

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

With the tasks outside work controlled for, the marginal effects of tasks at work change in different directions in magnitude. In particular, workers who deal with a general complex task have 0.14 (an increase of 5.6th percentile from the mean) standard

and tasks at work on skill production. Estimates for the task interaction terms are mostly statistically insignificant. Therefore, we keep the current model without the interaction term in order to reduce multicollinearity.

deviation higher PS, which is larger than the estimate of 0.13 without tasks outside work controlled for. The marginal effect of analytical tasks at work is reduced to 0.08 standard deviation. The effect of the interactive tasks at work on PS remains insignificant.

As expected, interactive tasks outside work contribute positively to the growth of all three skills. In particular, a 10% increase in the share among the 4 interactive tasks outside work will lead to 0.07 (an increase of 2.8th percentile from the mean) standard deviation increase in PS. The significant effect of interactive tasks outside work on PS is consistent with our previous analysis that it captures the unobserved skills and preferences toward interactive tasks at work. However, the analytical tasks outside work have no significant impact on the formation of PS.

Including tasks outside work as a proxy for q can help partially reduce the unobserved heterogeneity. It is possible, though, that tasks outside work are not a perfect proxy, and then all the OLS estimates would be inconsistent. Alternatively, the Multiple Indicator (MI) approach may be better than the proxy variable approach because of its less restrictive consistency assumption to get consistent estimates for all variables (Wooldridge (2010).[33]

---

[33] If we have two indicators nw_I and nw_A for unobserved heterogeneity q, we use the multiple indicator approach to correct for unobserved heterogeneity in the model $h_t = \lambda H\kappa + w_t\beta_1 + \beta_4 ex_t + \delta a_t + q + u$, where w, ex, a, H could be endogenous. Assume the indicators have the following functional form: $nw_I = \gamma_0 + \gamma_1 q + a_I, nw_A = \rho_0 + \rho_1 q + a_A$. After replacing q with nw_I or nw_A, we have the new model: $h_t = \lambda H\kappa + w_t\beta_1 + \beta_4 ex_t + \delta a_t - \frac{\gamma_0}{\gamma_1} + \frac{1}{\gamma_1} nw_I - \frac{1}{\gamma_1} a_I + u$. Under the assumptions of $Cov(a_I, a_A) = 0$, $Cov(a_I, q) = 0, Cov(a_A, q) = 0$, i.e., nw_I and nw_A are not correlated after netting out the q, we could use nw_A as instrument for nw_I because it satisfies $Cov(a_A, -\frac{1}{\gamma_1} a_I + u) = 0$ and $Cov(nw_I, nw_A) \neq 0$.

The key assumption for the MI approach is that the interactive tasks and analytical tasks outside work are not correlated netting out the common q that influences both of them, i.e., $Cov(a_I, a_A) = 0$. This assumption stands when interactive tasks outside work and analytical tasks outside work are determined by different personal traits after we net out the common ability, motivation, and preference q. In particular, workers who live a long distance from family are more inclined to do interactive tasks outside work including online chatting or emailing, while they don't necessarily prefer to do analytical tasks outside work such as reading financial documents. Therefore, we use tasks outside work as indicator for the unobserved heterogeneity and apply the MI approach. A similar approach is applied in Blackburn and Neumark (1992), which used two intelligence test scores, IQ and Knowledge of the World of Work as indicators of ability to estimate the wage equation.

Asymptotically, it is consistent to choose either interactive tasks or analytical tasks as the indicator, but the results may differ in a finite sample. We treat each of them as the indicator and the results are reported in Table 19. The coefficient estimates for our variable of interest in the MI models are quite similar with a difference at the second decimal points, although analytical tasks at work turn insignificant when we use analytical tasks outside work as included indicator in the model.

The results show that the complex tasks at work still contribute positively to the formation of PS and the effects remain similar in magnitude to the earlier OLS estimation. More specifically, workers with more complexity at work have 0.15-0.17 standard deviation higher PS.

Table 19 – Multiple Indicator Approach-PIAAC Germany

Dependent variable:	PS	PS
Complex task at work	0.145**	0.169**
	(0.0502)	(0.0559)
Interactive task at work	-0.0122	-0.00861
	(0.0132)	(0.0151)
Analytical task at work	0.0807***	-0.00422
	(0.0120)	(0.0188)
Interactive task outside work	0.0765**	
	(0.0260)	
Analytical task outside work		0.319***
		(0.0436)
Experience	0.0164*	0.0149
	(0.00900)	(0.0101)
Experience*Age	-0.000583***	-0.000632***
	(0.000144)	(0.000166)
High school	0.450***	0.364**
	(0.114)	(0.121)
Bachelor	0.818***	0.741***
	(0.120)	(0.129)
Master or above	1.081***	0.977***
	(0.122)	(0.132)
Female	-0.0921**	-0.0392
	(0.0447)	(0.0533)
Mother with high school or above	0.226***	0.211***
	(0.0514)	(0.0586)
Father with tertiary education	0.0972**	0.0989*
	(0.0439)	(0.0529)
_cons	-1.472***	-1.517***
	(0.196)	(0.146)
Industry dummies	Yes	Yes
N	1598	1598
First-stage coefficients of excluded instruments		
Interactive task outside work	0.481***	
	(0.035)	
Analytical task outside work		0.221***
		(0.15)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Likewise, the analytical tasks at work only contribute to 0.08 standard deviation higher PS. When we use interactive tasks as the included indicator, the estimates and significance levels are also quite similar to the results with tasks outside work added as proxy variable. Our MI results regarding the effects of tasks at work on PS are consistent with the previous analysis.

3.5.3 Instrumental Variable Estimation

The MI approach will be biased when the remaining residual from tasks outside work may still be correlated with other regressors, after using them as indicators. Therefore, concerning tasks outside work may not be a perfect proxy, we also applied the general IV estimation to the model with tasks outside work controlled.

In general, if good instruments can be found, i.e., $Cov(w_t, z) \neq 0, Cov(z, q+u) = 0$, the IV estimation will provide consistent estimation.[34] We consider potential instruments from the exogenous factors that influence the frequency and types of tasks at work but are not directly related to an individual worker's skills. Valid instruments are derived from available information on the demand side, e.g., the job requirements on tasks, and some exogenous changes in the work place (e.g. change in the number of colleagues).

Table 20 shows the summary statistics of instrumental variables for German workers. Specifically, in the PIAAC, workers are asked to report the usual education qualifications if applying today, someone would need to get for the type of their current job. The education required to get a particular type of job provides information on the demand for complex tasks at work, generally applicable to all employees with the same occupation. The education requirement doesn't change or vary with an individual

[34] One may also be concerned that there is a simultaneity issue between skills and tasks at work, i.e., there is a joint determination between high skilled workers and solving complex tasks at work. However, our case is unlike the simultaneity between prices and quantity in econometrics because employers usually don't observe workers' problem-solving skill scores directly. Nevertheless, the instrumental variable approach helps address the possible simultaneity issue.

employee or job applicant and therefore is not directly correlated to any individual worker's unobserved skill. Workers report that the average requirements that someone would need to get their current type of job is 14.1 schooling years, or a college degree, if applying today.

Table 20 – Instrumental Variables-PIAAC Germany

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Required schooling years	If applying today, the usual qualifications in schooling years, if any, that someone would need to get this type of your current job	1582	14.12	3.01	9	22
Change in colleagues	1 if over the last 12 months, the number of people working at the place where you work either increased or decreased	1560	0.448	0.497	0	1
Importance of analytical task at occupation level	The average standardized importance scale of analytical tasks at occupation level from O*NET in USA	1591	0.320	0.754	-1.7	1.7
Importance of interactive task at occupation level	The average standardized importance scale of interactive tasks at occupation level from O*NET in USA	1591	0.097	0.828	-1.1	2.4

Another set of instruments is the change of colleagues in the workplace. Changes in the work force are determined by market demands for the products/services of the firm and by local labor market conditions. An increase in the number of colleagues will require workers to do more interactive tasks at work, but would not directly be related to an individual worker's unobserved skills. Therefore, we use a dummy variable indicating the change in the number of people working at the work place over the last 12 months; it could reflect the necessary social interactions or coordination among coworkers.

We construct two additional instruments on importance of analytical and interactive tasks at the occupation level. The employers design the job tasks and set the job requirements, generally applicable to all employees in the same occupation; these should not be directly correlated with the applicants' unobserved heterogeneity. Our data is based on data from the literature, Acemoglu and Autor (2011) calculates the standardized score of composite measures of O*NET Work Activities and Work Context Importance scales at the 1990 Census occupation level in the USA. It represents the importance and requirements of analytical and interactive tasks in a specific occupation. We map the 337 1990 census occupations into 40 occupations in the PIAAC, and average the standardized importance scores across the fitted occupations in the data, to get the average importance scales of analytical and interactive tasks at the PIAAC occupation level.

Furthermore, given that the task requirements at the occupational level should share some similar features across countries, we use the O*NET task importance scales at the occupational level as instruments for workers' task intensity in Germany. It's similar to the methods in Goos and Manning (2007), Goos, Manning and Salomons (2009), and Goos, Manning and Salomons (2014): they use the task characteristics at the occupational level, which are derived from the US datasets, to proxy for the task content in European countries including Germany.

The first stage results in Table 21 show that the required education to apply for one's current job is positively correlated with all the task complexity measures. As expected, a change in colleagues will lead to an increase in interactive tasks at work; in addition, the occupational importance scales in analytical and interactive tasks at work have strong predictive power for the individual involvement in analytical and interactive tasks at work. We checked the redundancy of excluded instruments and did the over-identification tests; the instruments are both individually and jointly closely related to the complex task measures at work. They cannot reject the null hypothesis of the overidentification test at the 30% significance level.[35] Moreover, the exogeneity assumptions of tasks at work are rejected.

Table 21 – First-Stage Regressions of Instrumental Variable Approach-PIAAC Germany

Dependent variable:	Complex task at work	Interactive task at work	Analytical task at work
Required schooling years	0.036***	0.214***	0.205***
	(6.14)	(9.65)	(8.43)
Change in colleagues	0.039	0.181*	0.174
	(1.82)	(2.14)	(1.88)
Occupational analytical task importance	0.101***	-0.085	0.487***
	(4.63)	(-0.96)	(5.29)
Occupational interactive task importance	0.036*	0.543***	-0.061
	(2.44)	(8.71)	(-0.82)
N	1539	1539	1539

Note: we only report the results for outside instruments here. We report t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results for PS are reported in Table 22. These results are overall consistent with the results from the previous proxy variable and MI approach.

[35] The test on redundancy of excluded instruments uses a formulation based on testing the rank of the matrix cross-product between the endogenous regressors and the possibly-redundant instruments after both have all other instruments partialled-out. The test statistic is an LM test and numerically equivalent to a regression-based LM test. The over-identification tests report Hansen's J statistic, it allows observations to be correlated within groups. For the endogeneity test, the test statistic is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous, it's robust to various violations of conditional homoscedasticity. We use robust standard errors; the above test statistics are all robust.

Table 22 – Instrumental Variable Approach and Combination of Multiple Indicator & Instrumental Variable Approach-PIAAC Germany

	Instrumental Variable Approach	Multiple Indicator & Instrumental Variable Approach
Dependent variable:	PS	PS
Complex task at work	0.261	0.111^{*}
	(0.883)	(0.0623)
Interactive task at work	-0.101	0.0227
	(0.0776)	(0.0554)
Analytical task at work	0.283^{*}	0.0680^{**}
	(0.153)	(0.0261)
Interactive task outside work	0.0688^{***}	0.0708^{**}
	(0.0125)	(0.0265)
Analytical task outside work	-0.0720	
	(0.0574)	
Experience	0.0109	0.0162^{*}
	(0.0112)	(0.00963)
Experience*Age	-0.000506^{**}	-0.000585^{***}
	(0.000172)	(0.000152)
High school	0.402^{**}	0.424^{***}
	(0.128)	(0.119)
College	0.640^{***}	0.785^{***}
	(0.144)	(0.130)
Master or above	0.846^{***}	1.051^{***}
	(0.155)	(0.132)
Female	-0.0741	-0.0999^{**}
	(0.0616)	(0.0469)
Mother with high school or above	0.176^{**}	0.224^{***}
	(0.0603)	(0.0516)
Father with tertiary education	0.0802	0.102^{**}
	(0.0528)	(0.0450)
_cons	-1.492^{***}	-1.479^{***}
	(0.165)	(0.199)
Industry dummies	Yes	Yes
N	1539	1553
Endogeneity test: Chi-squared test & p-value	15.97 (0.001)	
Overidentification test of instruments: Chi-squared test & p-value	1.00 (0.317)	3.172 (0.075)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Workers who deal with a complex analytical task at work are expected to have a 0.28 standard deviation higher PS (an increase of 11th percentile from the mean). The general measure of complex job still has a positive and enlarged impact on problem-solving skills but turns to be insignificant.

Although the IV estimation presumably produces consistent results, it's hard to find the strong IVs. When we use the MI approach to address the unobserved heterogeneity, we assume that the remaining residual from the included indicator is uncorrelated with all the tasks at work. However, the remaining residual e.g., a_I from interactive task outside work may be related to interactive task at work. For example, the individuals who live far away from home are more likely to do online chatting at work. Therefore, we did a more careful estimation which accounts for the remaining residual related to tasks at work in addition to endogenous regressors due to unobserved heterogeneity. In addition to using analytical tasks outside work nw_A as IV, we need to find instruments for interactive task at work. Compared to instrumental variable approach with all the instruments from the job demand information, it puts less restriction on the number of IVs for identification. The detailed derivation and assumptions are discussed in Appendix A.

For interactive task measures at work, we choose from our previous IV list the change in colleagues and O*NET occupational interactive task importance. Our new estimates are also reported in Table 22 for PS. The first stage results are included in Table 23.

Table 23 – First-Stage Regressions of Combination of Multiple Indicator & Instrumental Variable Approach-PIAAC Germany

Dependent variable:	Interactive task at work	Interactive task outside work
Analytical task outside work	0.027	0.486^{***}
	(1.21)	(13.74)
Change in colleagues	0.105	0.092
	(1.35)	(0.79)
Occupational interactive task importance	0.510^{***}	0.168^{*}
	(10.04)	(2.20)
N	1553	1553

Note: we only report the results for outside instruments here.
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results are quite similar to our previous MI results, though with a reduced magnitude. More specifically, the marginal effect of the general complex tasks measure decreases from 0.144 to 0.11, and the marginal effect of analytical tasks at work changes from 0.081 to 0.068. This is still consistent with our previous analysis that PS is accumulated from solving complex tasks at work.

In summary, we use multiple empirical approaches under different assumptions to estimate the effects of task complexity on general problem-solving skills. We first relax the perfect proxy assumption and use tasks outside work as additional proxy for unobserved heterogeneity q. We further relax the perfect proxy assumption and instead use tasks outside work as indicators for q; assuming tasks outside work can remove the correlation between q and other endogeneous regressors, we apply the multiple indicator approach. Furthermore, the instrumental variable approach is applied to addresses the endogeneity of job tasks in a more general way; it deals with issues such as omitted variable bias and reverse causality. Considering the requirements for the IVs are quite strong, we combine the Multiple Indicator approach and IV approach, and use the detailed information on the unobserved heterogeneity to do a more efficient estimation.

Our results show that workers accumulate their problem-solving skills through performing complex tasks at work with an increase of a 4.4th-6.0th percentile increase from the 50th percentile in the skill distribution. The analytical tasks at work are expected to contribute to an additional improvement in problem-solving skills, which is a 2.8th-11th percentile increase from the mean. However, the interactive tasks show no significant impact on all the estimations.

3.6 Job Task Complexity and Complex Problem-solving Skills-Further Investigation based on LLLight'in'Europe project Data

To further investigate how job task complexity on different levels of problem-solving skills, another dataset that we use is from the LLLight'in'Europe project (LLL). This project built a unique measure of complex problem-solving skills (CPS), which is regarded as a higher level of problem-solving skills.[36] Complex problem-solving is measured based on the definition of Buchner (1995) "the successful interaction with task environments that are dynamic and in which some of the environment's regularities can only be revealed by successful exploration and integration of the information gained in

[36] The LLLight'in'Europe project is part of the European Commission's 7th Framework Program for Research and Technological Development. The project aims to investigate the role of lifelong learning on human capital accumulation and labor market outcomes. It is a cooperation of 9 European and international research institutions, and is furthermore supported by the OECD and Cedefop. It collected the information of 1129 individuals from 43 companies and organizations in 37 countries. More details can be found on the project website: http://www.lllightineurope.com/home/general-information/

that process".[37] Therefore, it will help us get a deeper understanding on the accumulation of problem-solving skills.

We restrict our sample to workers in Germany because Germany has the largest sample in the LLL dataset and also their results can be comparable to our previous results with the PIAAC Germany data. The summary statistics are reported in Table 24.

Compared to the PIAAC sample shown in Table 12, we have a larger more-educated sample in the LLL project, i.e., a higher percentage of workers finished their highest degree at junior school or below (64%), while that portion is only 27% in the PIAAC. The workers in the LLL project are more representative of junior workers because they have an average age of 35.4 years, 5 years younger than that of workers in the PIAAC. They have 13.2 years of total work experience on average, 6 years less than that in the PIAAC. Different from the PIAAC, we have the additional information on the number of occupation titles held: 46% of the sample worked only in one occupation title, 83% worked in two.

[37] The project team constructs the CPS measure based on two psychometric tests MicroDYN and/or MicroFIN. The two phases are involved in both the MicroFIN test and MicroDYN test: (1) knowledge acquisition phase: individuals freely explore the simulation, followed by an assessment of the acquired knowledge; (2) knowledge application phase: individuals are asked to reach given target states, to assess their capabilities in applying the acquired knowledge. Therefore, it has dynamic interaction and interactive changes in the problem as defining characteristics, and requires computer-based assessment.

Table 24 – Variable Definition and Summary Statistics-LLL Germany

Variables	Definitions	Obs	Mean	Std. Dev.	Min	Max
Experience	Total number of work experience	384	13.2	10.9	0	42
Number of occupation titles had	Number of occupation titles he/she had worked in. The maximum number of 6 may include the case of 7 or above	384	1.9	1.2	1	6
Years-current employer	Years worked for the current employer	262	9.3	9.1	0	38
Middle school or below	1 if middle school education or below	384	0.279	0.449	0	1
High school	1 if high school diploma	384	0.031	0.174	0	1
College	1 if college degree	384	0.643	0.480	0	1
Master or above	1 if master degree or above	384	0.047	0.212	0	1
Female	1 if female	384	0.216	0.412	0	1
Age	Age	384	35.4	12.6	18	65
Parent with a tertiary education	1 if highest education for at least one of parents is college or above	384	0.411	0.493	0	1
Service industry	1 if work in service industry	384	0.294	0.456	0	1

Source: the LLLight'in'Europe project (LLL), 2013-2015, Germany.
Note: 1. For the variable "parent with a tertiary education", if the education information for one parent is missing, we use the other parent's information as a substitute. Similar method is applied to deal with the missing values for some other variables such as task complexity at work.

Table 25 shows the summary statistics for complex problem-solving skills. The complex problem-solving scores range from 280-690 points, and the average score is 516. Similar to problem-solving skills in the PIAAC, complex problem-solving skills show a mild improvement with a 12 points' increase in the first 8 years of working experience in Table 13. We also use its standardized scores for regression.

Table 25 – The Dynamic Trend with Experience-LLL Germany

Variables	Definitions	Obs	Mean	Std. Dev.	Min	Max
CPS-total	Overall complex problem-solving skills (CPS)	384	516.3	94.5	289.6	689.4

Total years of experience	Obs	CPS
0-3	111	535.1
4-7	58	547.4
8-11	71	525.7

In the LLL survey, workers report how frequently they perform 10 interactive tasks, and 13 analytical tasks at work. They are identical to the questions included in the PIAAC while the PIAAC has relatively more tasks included. The details on the selected tasks are shown in Table 26.

We choose those job activities and follow the same principle to define the complexity of interactive and analytical tasks at work: a worker is considered to deal with a more complex interactive task at work if he/she performs a higher percentage of 10 interactive tasks at work at the same time.

Table 26 – Tasks at Work-LLL Germany

Interactive tasks at work:
1.Sharing work-related information with co-workers
2.Instructing, training or teaching people, individually or in groups
3.Making speeches or giving presentations in front of five or more people
4.Advising people
5.Planning the activities of others
6.Persuading or influencing people
7.Negotiating with people either inside or outside your firm or organization
8.Read letters memos or emails
9.Write letters memos or emails
10.Selling a product or selling a service
Analytical tasks at work:
1.Read directions or instructions
2.Read professional journals or scholarly publications
3.Read manuals or reference materials
4.Read bills, invoices, bank statements or other financial statements
5.Read diagrams maps or schematics
6.Write reports
7.Fill in forms
8.Calculating prices, costs or budgets
9.Use or calculate fractions, decimals or percentages
10.Use a calculator, either hand-held or computer based
11.Prepare charts graphs or tables
12.Use simple algebra or formulas
13.Use advanced math or statistics such as calculus, complex algebra, trigonometry or using regression techniques

Note: The LLL project asks how often individuals perform the type of task in their job. The options include: 1 Never; 2 Less than once a month; 3 Less than once a week but at least once a month; 4 At least once a week but not every day; 5 Every day.

Table 27 shows the task measures in LLL. We define a general complex task measure identical to that in the PIAAC: 67.2% of the LLL samples frequently deal with complex problems at work if they deal with more complex problems, which take at least 30 minutes to think of a good solution, for at least once a month. The number is quite similar to the number of 68.9% in the PIAAC samples.

Table 27 –Summary Statistics of Tasks at Work-LLL Germany

Variables	Definitions	Obs	Mean	Std. Dev.	Min	Max
Complex task at work	1 if confronted with more complex problems that take at least 30 minutes to think of a good solution at least once a month at work	384	0.672	0.47	0	1
Complexity of problems solved	Average minutes you usually need to find a solution to the problems you face daily in your job	384	14.0	10.7	2.5	40
Interactive task at work	Share of tasks performed at least once a week among 10 interactive tasks at work	384	0.427	0.223	0	1
Analytical task at work	Share of tasks performed at least once a week among 13 analytical tasks at work	384	0.372	0.221	0	1

Note: 1. We treat the inconsistencies in workers' responses to two questions on task complexity at work and make some minor adjustments, i.e., if the workers report both "I usually need more than 30 mins to find a solution to the daily problems at work" and "I, never or for less than once a month, face more complex problems that take at least 30 mins to find a good solution", we correct the average time needed to find a solution to the problems you face daily at work by lowering its level to be "Between 20 and 30 minutes"; if the workers report both "I usually need no more than 5 mins to find a solution to the daily problems at work" and "I face more complex problems that take at least 30 mins to find a good solution every day", we correct the average time needed to find a solution to the problems you face daily at work by raising its level to be "Between 5 and 10 minutes". 3. We impute the missing value in the answers to the question "How often do you usually face more complex problems that take at least 30 minutes to find a good solution?" to be 1 if he/she reports more than 10 minutes for the question "How much time do you usually need to find a solution to the problems you face daily in your job?", 0 otherwise.

When we compare the complexity of job tasks for samples in the LLL (Table 27) and the PIAAC (Table 14), it's easy to find that the LLL samples deal with interactive and analytical tasks with less complexity at work. More specifically, on average, workers in the LLL project deal with 42.7% of 10 representative interactive tasks, and they deal with 37.2% of analytical tasks at work at least once a week at work. The numbers are relatively higher for the PIAAC samples, where the ratios are 47.7% of 13 interactive tasks, and 41.0% of 18 analytical tasks, respectively.

The general complex measure captures other job task characteristics than analytical and interactive tasks at work, there is a moderate overlap between them since the correlation coefficient between the general complex task measure and the interactive (analytical) task complexity measure is only 0.24 (0.21).

Table 28 shows the results with parents' education as a proxy for initial skills. In the first column, we add only the general task complexity measure and follow the same model specification as PIAAC. When we compare it with the baseline results in PIAAC (first column, Table 18), it seems the general complexity measure of the job doesn't have a significant effect on workers' complex problem-solving skills. The effect's magnitude is only 0.12 standard deviation, which is much smaller than the number of 0.26 standard deviation for PS. It is consistent with our expectation that it's much harder to accumulate complex problem-solving skills.

The estimates for education degrees and parents' education are as expected positive and significant. The results show that the gap in CPS is mainly between workers with a college degree or above and those without it. Female workers seem to have 0.6 standard deviation lower CPS; the possible reason is a less representative female sample, accounting for only 22% of the total sample. Also, when we use the same specification of experience and the interaction term between age and experience in the PIAAC model, the return of work experience to complex problem-solving skills will depreciate with aging from 19 years old.[38]

The second column adds the number of occupations worked to capture the variety of on-the-job learning, the result shows that the number of occupations held doesn't seem

[38] We also try another specification with the age and age squared to capture the dynamic growth of complex problem-solving skills. The marginal effects of tasks at work are smaller compared to the results with our current model setup. There seems to be a concave relationship between age and complex problem-solving skills, and the CPS starts to decline at 32 years of age.

to affect the CPS significantly.[39] The task complexity at work still contributes positively to a higher level of complex problem-solving skills with a smaller magnitude and the effect remains to be insignificant.

We include all three job complexity measures in the last column, and it produces consistent results with the PIAAC results: Interactive tasks at work have no significant effect on CPS. Workers who deal with 10% more analytical tasks at work with a frequency of at least one week or above have 0.04 standard deviation higher CPS, half the size of the effect for PS. It indicates that complex problem-solving skills are more difficult to accumulate with analytical tasks.

The LLL survey provide additional information on the time the worker usually needs to find a solution to the work problems, based on it we construct a continuous general task complexity measure with the average minutes to find a solution to the problems the workers face daily in their job. According to Table 27, it takes workers 14 minutes on average to figure out a solution for daily work problems. For the robustness check, we did the OLS regression with the new general task complexity measure in Column 1, Table 28. The results for interactive tasks and analytical tasks are quite consistent. The results show that with 20 minutes increase in the time to solve daily work problems, the workers are expected to have 0.10 standard deviation higher CPS although it's only 17% statistically significant.

[39] When we drop the number of occupations held, the marginal effects of tasks at work become smaller at the three decimal points. It suggests a negative relationship between the number of jobs held and the task complexity at one's current job, i.e., less able workers change employers more.

Table 28 – Baseline Results of Complex Problem-solving Skills & Tasks at Work-LLL Germany

Dependent variable:	CPS	CPS	CPS	CPS	CPS
Complex task at work	0.120	0.125		0.0968	
	(0.0946)	(0.0971)		(0.0963)	
Complexity of problems solved					0.00566
					(0.00377)
Interactive task at work			-0.00190	-0.00490	-0.00134
			(0.0246)	(0.0245)	(0.0248)
Analytical task at work			0.0448**	0.0428**	0.0450**
			(0.0215)	(0.0217)	(0.0217)
Experience	-0.0213	-0.0275	-0.0297	-0.0287	-0.0315
	(0.0227)	(0.0235)	(0.0241)	(0.0240)	(0.0243)
Experience*Age	-0.000280	-0.000204	-0.000146	-0.000160	-0.000107
	(0.000392)	(0.000402)	(0.000409)	(0.000406)	(0.000412)
Number of occupations worked		0.0397	0.0582	0.0561	0.0598
		(0.0374)	(0.0384)	(0.0383)	(0.0381)
High school	0.124	0.103	0.138	0.109	0.127
	(0.297)	(0.293)	(0.289)	(0.286)	(0.285)
College	0.867***	0.857***	0.837***	0.822***	0.802***
	(0.109)	(0.114)	(0.114)	(0.115)	(0.117)
Master or above	1.371***	1.312***	1.295***	1.267***	1.248***
	(0.162)	(0.171)	(0.173)	(0.173)	(0.175)
Female	-0.604***	-0.603***	-0.604***	-0.586***	-0.576***
	(0.102)	(0.103)	(0.103)	(0.104)	(0.104)
Parent with a tertiary education	0.170**	0.161*	0.170**	0.161*	0.173**
	(0.0836)	(0.0850)	(0.0853)	(0.0850)	(0.0850)
_cons	-0.254**	-0.281**	-0.385**	-0.419**	-0.452**
	(0.123)	(0.125)	(0.143)	(0.147)	(0.148)
Industry dummies	Yes	Yes	Yes	Yes	Yes
N	391	384	384	384	384
adj. R^2	0.390	0.387	0.390	0.390	0.392

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In addition, considering that the parents' education may not capture the unobserved individual ability, we apply the instrument variable approach with valid instruments for tasks at work. The summary statistics of instruments are listed in Table 29. Workers report the number of times that the new equipment or new computers have been introduced in the workplace. They are supposed to lead to the change in job content, and new challenging interactive and analytical tasks at work. Furthermore, reorganization of work environment, or change of new direct supervisor may also lead to changes in the job task allocations. Therefore, they can act as valid instruments for job tasks performed at individual level. Following the same arguments as in PIAAC, we also use the importance scales of interactive and analytical tasks by occupation from O*NET in the USA as instruments.

Table 29 – Instrumental Variables-LLL Germany

Variable	Obs.	Mean	Std. Dev.	Min	Max
In the last 12 months, frequency of					
1. the introduction of new equipment or new computer programs in your company	376	2.88	7.08	0	100
2. the basic restructuring or reorganization affecting your work environment	376	1.73	6.47	0	100
3. the introduction of new or clearly modified products or material	376	2.53	9.39	0	100
4. getting a new direct supervisor	376	0.40	1.24	0	12
The average standardized importance scale of analytical tasks at occupation level from O*NET in USA	376	0.62	0.79	-0.96	1.69
The average standardized importance scale of interactive tasks at occupation level from O*NET in USA	376	0.13	0.878	-0.98	2.40

The first stage results of our instruments are shown in Table 30. It seems the occupational analytical and interactive task importance scales have a high predictive power on the complex job tasks performed at individual level.

Table 30 – First-Stage Regressions of Instrumental Variable Approach-LLL Germany

Dependent variable:	Complex task at work	Complexity of problems solved	Interactive task at work	Analytical task at work
Introduction of new equipment or new computer programs	0.008	0.055	-0.012	-0.038
	(0.22)	(0.72)	(-0.30)	(-1.03)
Basic restructuring or reorganization affecting your work environment	0.022	0.020	-0.005	-0.035
	(0.87)	(0.39)	(-0.19)	(-1.10)
Introduction of new or clearly modified products or material	0.043	0.033	-0.027	0.053
	(1.28)	(0.42)	(-0.84)	(1.36)
Getting a new direct supervisor	-0.043	-0.026	0.034	-0.063
	(-0.92)	(-0.46)	(0.79)	(-1.71)
Occupational analytical task importance	0.115	0.342^{***}	-0.082	0.072
	(1.64)	(4.95)	(-1.41)	(1.08)
Occupational interactive task importance	0.121^{*}	-0.164^{*}	0.458^{***}	0.112^{*}
	(2.13)	(-2.25)	(8.95)	(2.07)
N	376	376	376	376

Note: we only report the results for outside instruments here. *t* statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31 shows the IV results using two different general task complexity measures. The results using the identical general task definition show that the general task complexity has the most important and significant impact on complex problem-solving skills. It rejected the exogeniety assumptions and cannot reject the null hypothesis of overidentification test at 37% significance level. When we use the average minutes to solve daily problems as a measure for the general job complexity, the results indicate that with 10 minutes increase in the task complexity, a worker's complex problem-solving skills will increase by 0.64 standard deviation (an increase from 50th percentile to 74th percentile). The interactive and analytical tasks are positive but both insignificant.

Table 31 – Instrumental Variable Approach-LLL Germany

Dependent variable:	CPS	CPS
Complex task at work	2.579*	
	(1.486)	
Complexity of problems solved		0.0636**
		(0.0304)
Interactive task at work	-0.0398	0.178
	(0.106)	(0.155)
Analytical task at work	-0.0846	0.0307
	(0.401)	(0.425)
Experience	-0.00900	-0.0921**
	(0.0493)	(0.0407)
Experience*Age	-0.000481	0.000917
	(0.000872)	(0.000592)
Number of occupations worked	-0.0311	0.0635
	(0.173)	(0.165)
High school	-0.550	-0.0697
	(0.512)	(0.296)
Bachelor	0.501	0.222
	(0.305)	(0.268)
Master or above	0.645	0.604
	(0.448)	(0.411)
Female	-0.149	-0.318
	(0.296)	(0.213)
Parent with a tertiary education	-0.111	0.126
	(0.190)	(0.108)
_cons	-1.054	-1.363
	(1.081)	(1.171)
Industry dummies	Yes	Yes
N	376	376
Endogeneity test: Chi-squared test & p-value	20.52	24.00
	(0.00)	(0.00)
Overidentification test of instruments: Chi-squared test & p-value	3.16	0.58
	(0.367)	(0.90)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Conclusions

Despite the informal arguments that learning by doing is important for improving workers' skill sets and can get workers better prepared for the upgrading of job contents with advanced technological change, there is little research directly linking the heterogeneity in job tasks at individual level and individual skill measures due to the lack of such micro datasets. This paper provides a first step in this direction and tries to empirically demonstrate the contribution of job tasks to an individual's problem-solving skills. We test the existence of dynamic learning with job tasks using two datasets for Germany. These two datasets provide two measures of problem-solving skills at different levels: general problem-solving skills and complex problem-solving skills.

Estimates using both skill measures indicate that workers with a complex job can accumulate their problem-solving skills more. In particular, solving complex problems for at least once a month accounts for a 4^{th}-6^{th} percentile increase in the skill distribution. The additional effect associated with a complex analytical task relative to a general complex job is a 3^{th}-11^{th} percentile increase in the skill distribution, while interactive job tasks do not have a significant effect.

Our findings on complex problem-solving skills show that task complexity can also contribute to a higher level of problem-solving skills but with a much smaller magnitude. The results indicate that it's more difficult to accumulate skills to solve more complex problem, and there is a decreasing marginal effect of learning via tasks as the level of skills increases.

CHAPTER 4 THE LABOR MARKET EFFECT OF TERTIARY EDUCATION FOR FULL-TIME WORKERS

4.1 Introduction

Human capital accumulation is considered to occur mainly through formal education and training (which includes on-job learning-by-doing). Traditionally, these channels are sequential and separated in time, i.e., an individual first receives formal education in school, then receives job training and acquires work-related skills while performing the job. Education programs for full-time workers (or on-job education), however, provide adult workers with another sequence with more flexibility, receiving formal education while at work, instead of quitting job for a full-time study (or regular education). Colleges and universities are developing various degree programs aimed at working professionals. The recent rapid growth in internet-based education such as MOOC makes it even easier than it was before for workers/professionals to obtain formal higher education while at work.

There exist various forms of adult learning in Organization for Economic Cooperation and Development (OECD) countries (Belanger and Tuijnman 1997). In countries like US, Sweden, the common case is students usually work while in school (Light (2001); Sabia (2009); Avdic and Gartell (2015)). However, in China, almost all the students don’t work while at school, but a large number of workers with full-time employment study for tertiary degrees.

In China, the on-job education has developed under a special historic background: at the beginning of the economic reforms in 1978, there was a severe lack of workers with higher education, because a large number of adults had missed the chance of going to college during the Cultural Revolution. The Chinese government created a variety of continuing education programs to make it possible for these people to earn higher education degrees. Colleges and universities have made their degree programs available for those who have full-time jobs.

As a result, a large number of individuals received their degrees while at work. In 2010, 1.23 million working individuals enrolled in junior college (three-year college), accounting for around 40% of the regular new junior college enrollment. At the college level (4-year program for a Bachelor degree), the new enrollment of on-job students in the same year was 0.85 million, approximately 24% of the regular college new enrollment. For the on-job graduate students, the new enrollment in 2010 was 125,000, amounting to 30% of regular new enrollment of graduate students for that year.[40] Clearly, on-job education has been an important part of tertiary education in China.

This study investigates the difference in labor market effects for tertiary degrees obtained by those who are full-time workers compared to those who are full-time students. We used four waves of national representative survey data from the Chinese Household Income Project (CHIP) in 1995, 2002, 2007, and 2013 in the investigation. The samples cover a long period during the course of economic reform and rapid expansion of higher education in China (starting in 1999), and thus allow us to analyze the dynamics of the labor market effects.

[40] Data source: the China Statistical Yearbook of Education 2010, Ministry of Education.

The differences between the returns of learning full-time and learning while having a job have important implications for on-job schooling in particular, and for lifelong learning in general. More specifically, is it worthwhile for the individuals to spend time and effort in such education programs while working? Should the employers encourage employees to get a degree while at work via various policy incentives? This study is aimed to contribute answers to these questions.

Our study fits in the series of literature that estimate the impact of General Equivalency Diploma (GED) for exam-certified high school equivalents in the US, starting with Cameron and Heckman (1993). Cameron and Heckman (1993)finds that exam-certified high school equivalents are statistically indistinguishable from high school dropouts, and have lower return than high school graduates do. The following papers, to name a few, Heckman, Humphries and Kautz (2014), and Jepsen, Mueser and Troske (2016), provide a more comprehensive analysis of the labor market returns to the GED. Little research has been done about China in the difference of on-job education and regular education in China. One study investigates the effect of adult learning by comparing employees who received adult education in a local community-oriented center and those who didn't (Xiao 2002).

Therefore, our study attempts to provide a comprehensive investigation of labor market effects of different learning channels for full-time workers. Our study finds a significant difference in the return to schooling between regular students and on-job students. More specifically, the rate of return for an on-job graduate degree is around 23-25 percentage points lower than that for a regular graduate degree. The return to on-job learning at a four-year college level is 7-9 percentage points lower than that for regular learning. But we find a much smaller or no significant gap in returns between on-job and regular junior college degrees.

The paper proceeds as follows: we introduce the basic facts on China's higher education system for working adults. Then the paper presents the microdata and identification of workers who obtained degrees through on-job education. Based on the microdata, we describe the features of on-job education and demographic characteristics of individuals who chose it in more details. Next we describe our empirical model for comparing labor market outcome between on-job schooling and regular schooling. We also discuss the econometric evidence on the equivalence between on-job and regular degrees. In next section we address the unobserved heterogeneity and check the robustness of results. The proxy variable approach and control function approach are implemented. Then we further investigate the potential causes for the gap between regular and on-job education. Based on the empirical estimates on schooling returns, we also do a cost-benefit analysis on the on-job education choice. Then we conclude.

4.2 Tertiary Education Programs for Full-time Workers in China

In China, there are two main routes through which adults can obtain tertiary degrees: (a) through regular higher education program as a full-time student; (b) through on-job education for full-time workers. Tertiary education programs for working adults vary at different education levels. At the undergraduate level, the adult higher education system includes self-learning program, web-based college, radio and TV colleges, correspondence college, workers' college, college of education, etc. Similarly at the master level, we have programs for working adults such as Master of Business Administration (MBA), Master of Public Administration (MPA), Executive Master of Business Administration (EMBA), some law programs, etc. Workers could also pursue for a doctoral degree without quitting their jobs in China.

There exists disparity in types of institutions that offer programs, admission standards, program design, student learning patterns, and graduation certificates when we compare the tertiary education programs for working adults and regular education programs.

Working adults can get a tertiary degree at either a regular institution of higher education (regular colleges) or at an institution of higher education for adults (adult colleges). For example, since 1999 the Ministry of Education has authorized 68 regular colleges and Radio & TV colleges to offer degrees for web-based education. Until 2017, there are 283 adult colleges in China, compared to 2,631 regular colleges (including independence colleges). On average, relatively lower-ranking universities offer adult education programs; the case may be different at graduate level. The graduate programs for working adults are mainly offered by regular universities and usually top universities.

The tertiary education programs for working adults have the same requirements for applying for a regular education program in that the applicant should have a high school diploma to apply for a junior college program; and a high school or junior college degree to apply for college. However, their admission standards would be actually lower because the applicants take adult education entrance examinations at national or university level, which are less difficult than those for regular education programs. Also, students who choose the self-study program do not need to take the entrance exam.

To apply an on-job degree at the graduate level, on-job applicants can take the national entrance examination in January or the national Graduate Candidacy Test (GCT) in October, or join the on-job graduate student class with no entrance exam. At the doctoral level, they mostly need to take admission examinations designed by the school applied and national test of English proficiency and field knowledge. The admission standards for on-job education programs would be also lower because the entrance exams would be less difficult.

The minimum years required for graduation depends on the degree pursued, the education level the applicant currently has; it generally ranges from 2 to 3 years for junior college and 4 to 5 years for college degrees, which is similar to the regular education program design. However, they could provide more flexibility on the study schedule for the working adults. They take classes in the evenings and/or on weekends, or self-study through course materials, or via radio, TV, and Web. Students who choose the self-study program could secure a degree by passing the standardized course exams required by the on-job college education program. This offers students more flexibility on the class schedule and less strict requirements on graduation.

The on-job graduate degrees are designated to individuals who have working experience. More specifically, a bachelor’s degree is required to apply for a master program with over 3 years of working experience, and a master’s degree is required for a doctoral program, with over 5 years of working experience. On-job graduate students normally take courses in the first one or two years at school and then develop and write their thesis while at work. It takes at least 2.5 years to obtain an on-job degree at master level, the minimum years would be 2 years for a regular one; the maximum years of graduation for an on-job PhD is 8 years, longer than the 6 years' upper limit restriction for a regular one.

After finishing the education at the junior college and college level, the working adults will receive a graduation certificate offered by the colleges enrolled, either adult colleges or regular colleges. For the self-study program, the degree will be jointly offered by colleges and the National Committee on the Self-study Program. Therefore, a degree obtained through on-job education can be distinguished from the regular education diploma. At the master and doctoral level, the graduates will receive almost identical certificates as those for regular students so it would be harder to tell the difference based on their certificates.

There has been a fast development of tertiary education for working adults in China. Figure 6 plots the growth in the new enrollments of students with a full-time job at junior college or above. At junior college level, its new enrollments increased steadily from 0.91 million in 1997 to 1.77 million at around 2002, and then to its historic peak at 2.92 million in 2013. The new enrollments for college students maintained a faster growth during the period 1997-2014, growing by 19 times since 1997, and reaching 1.9 million in 2010. In addition, the number of master students shows a stable growth through 2002-2014 with an annual rate of 10% on average. As higher education expanded rapidly, especially after 1999, the education level of the labor force improved significantly. In particular, in 1999 alone, new undergraduate student enrollment increased 47%, and from 1999 to 2003, its average annual growth was 29% (Li 2010).

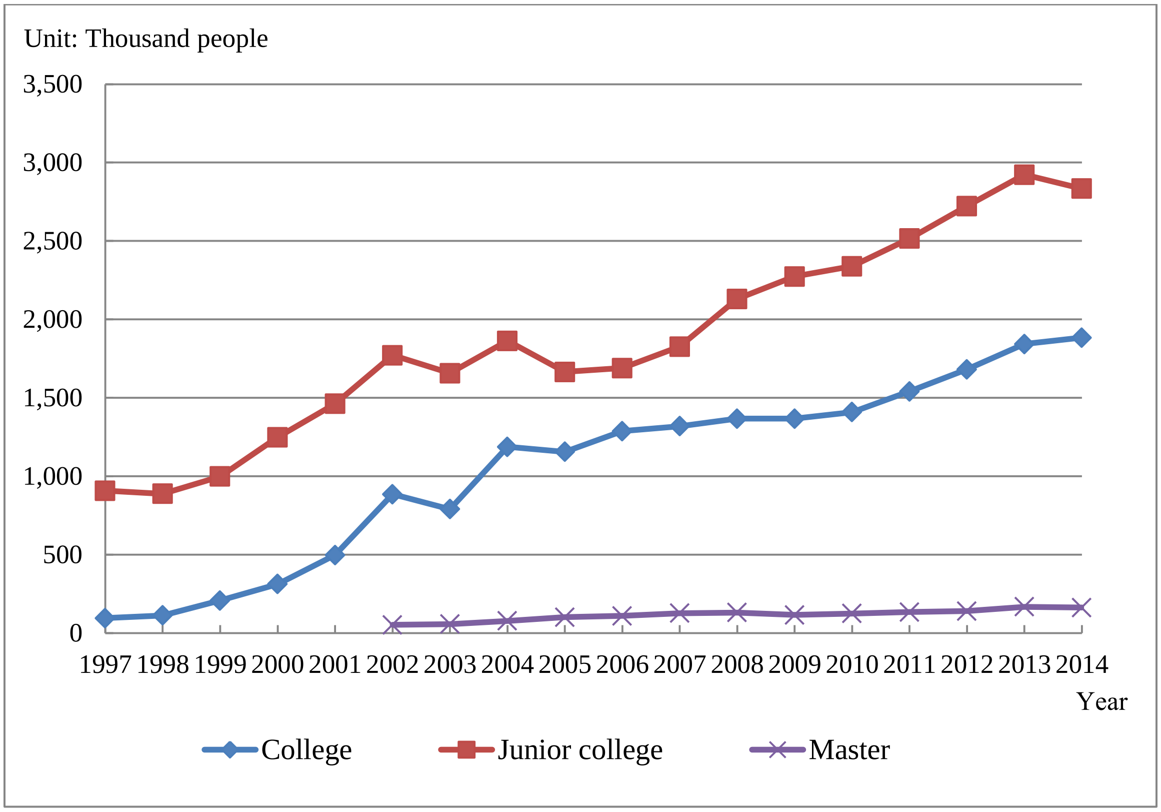


Figure 6 New Enrollments of On-job Students at Junior College or above

Notes:

1. On-job students at the college level are calculated by summing up of the adult college students and web-based college students. The similar calculations apply to junior college. We do not have the data before 2002 for the new enrollments for web-based college and web-based junior college, so we use the new enrollments of adult education students as a proxy for the new enrollments of on-job students at college and junior college level.
2. All the data are from the Statistical Yearbooks of Education for 1997–2014, Ministry of Education. For 2003, we cannot separate the on-job students at junior college and college levels with the original data, and thus imputed the data.

Figure 7 shows the relative trends of students who do schooling while having a job to regular students based on their new enrollments. Before 2002, the new enrollment of students pursuing a junior college degree while having a job was more than that of regular students; it more than doubled in 1997 and 1998. After that, its proportion declined rapidly to less than 70% in 2005 and has been quite stable since then. At the college level and graduate level, the relative new enrollments follow a steady pattern and ranges around 30-50% of the regular new enrollments with small fluctuations.

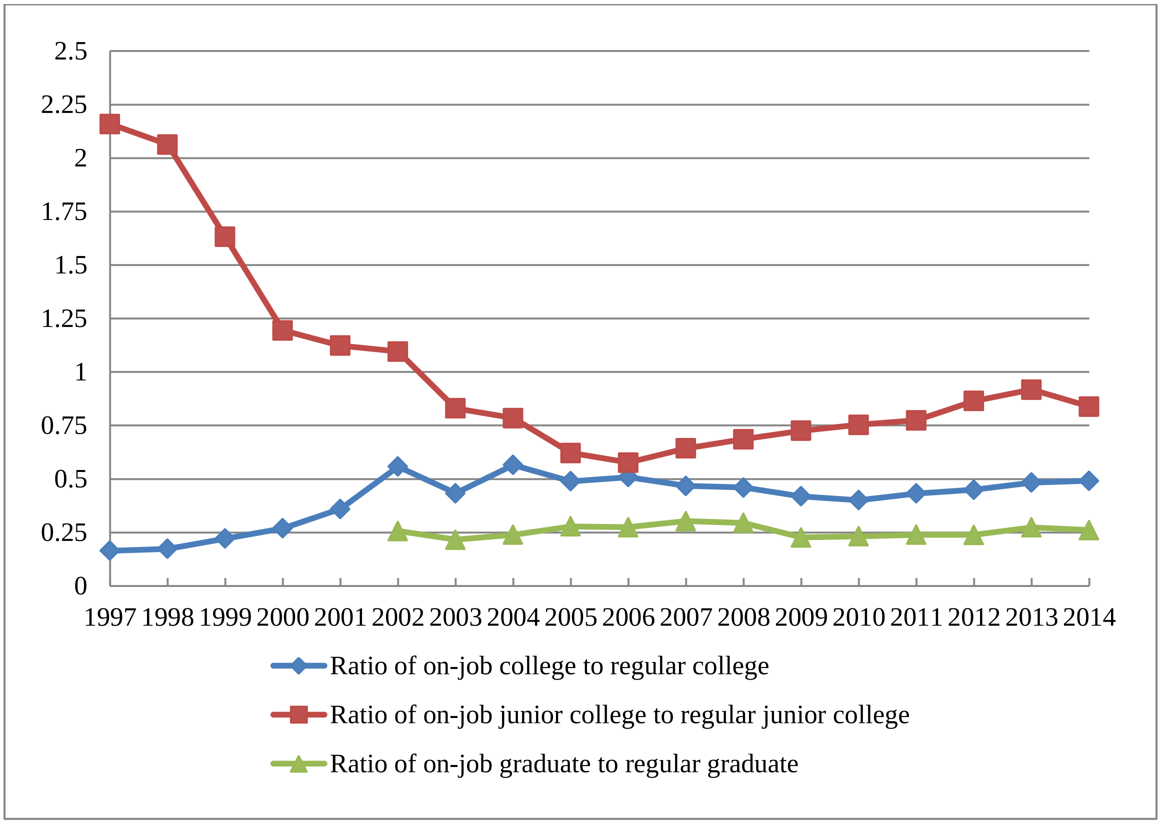


Figure 7 Ratios of On-job New Enrollments to Regular New Enrollments

Sources: The China Statistical Yearbooks of Education for 1997–2014, Ministry of Education.

On-job education is a significant part of higher education in China despite the slower growth compared to regular education. It would become more important in the future, due to the rapid advance of internet-based education delivery technology and the increase of on-line education programs for working individuals. For example, the web-based junior college new enrollments grow 8-fold from 2002 to 2014, and web-based college grows 3-fold, while the numbers change little for adult junior college and are only 2-fold for adult college.

The above trend reflects the historical background of higher education for working adults in China. In the early period of economic reform, there was a strong demand for workers with higher education, but the labor market for new entrants with a tertiary degree in higher education could not meet the demand. For example, in 1990, less than 1% of the labor force was at college level and 1.6% at junior college level. In this case, many working adult individuals chose to enroll in higher education programs to get degrees without quitting the job (and their employers had demands for them to obtain a higher degree too). It is easiest to get into a junior college degree program, because of the low pre-requisite, i.e., a high school diploma. That helps explain why this group has the largest percentage of on-job students.

4.3 Data and Samples

We used the urban samples of four waves of the Chinese Household Income Project (CHIP) for the years 1995, 2002, 2007 and 2013.[41] The CHIP is a well-known and widely used multi-year cross-sectional survey of households and individuals, with a focus on employment, income and other labor market aspects. The data produces national

[41] See the data website for details (http://www.ciidbnu.org/chip/index.asp). The data have been widely used in numerous studies; recent examples include Wang, Fleisher, Li, Li (2014), Gertler, Paul J., et al. (2016). We do not use CHIP 1988 in this study because the information on years of working experience is not available.

representative samples of urban and rural households.[42] We focus on individuals who completed the highest degree at higher education level, including junior college (3-year), college (4-year), and graduate degrees (master's or doctoral degrees). Our samples are restricted to full-time workers within the legal working age (females 16-55 years old and males 16-60 years old).[43]

In order to investigate the different labor market outcomes between those with a degree obtained via full-time studies and those studied without quitting a job, we need to identify those who received their degrees while at work. In particular, for CHIP 95 and CHIP 02, respondents are asked questions on the actual years of work experience, which we define as $ex_{actual} = a - s_1 - 6$. An individual would include the years when she/he worked on a job while studying for the degree at the same time as part of work experience. In addition, we use the schooling attainment and age information available to estimate the respondents' potential years of work experience, which is calculated as $ex_{potential} = a - s - 6$.[44][45] We then calculate the years of schooling while having a job s_2

[42] CHIP 95 and 02 cover 11 provinces including Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Sichuan (CHIP 02 has separated data for Chengdu and Sichuan), Yunnan, Gansu. CHIP 07 covers nine provinces/cities including Shanghai, Jiangsu, Zhejiang, Anhui, Henan, Hubei, Guangdong, Chongqing, and Sichuan. CHIP 13 includes 29 provinces/cities.

[43] We eliminate those with less than 20 working hours per week, and those who are proprietors and self-employed. We also eliminate those with earnings below the national minimum wage, because it is an extreme case given that our sample is for those with a higher education degree.

[44] If an individual has some time of unemployment, the potential years of experience might be overestimated. However, such a case makes it harder to put someone as receiving an education degree on-job. If someone with an on-job degree is regarded as having a regular degree, our estimation of the earning gap between those two groups should be a lower bound and thus our results should be strengthened. On the other hand, the unemployment rate is very low in China, especially for highly educated, and thus its impact in calculating potential experience should be very small. For example, only 4.3% in CHIP 02 samples did report previous periods of unemployment/laid off/absence from work. The regression results based on the on-job samples identified excluding those periods change very little.

[45] The self-reported years of schooling may differ from the expected years of completing an individual's highest degree, because the individual might have repeated or skipped some grades during the entire study. To reduce the reporting errors in the years of schooling, we limit the maximum years for skipping or repeating grades to be 3 years.

by $s_2 = ex_{actual} - ex_{potential}$. We use this information to determine whether the degree was completed while holding a job.[46]

The identification procedure for CHIP 95 and CHIP 02 still applies in CHIP 07 and 13. Because the survey questionnaires for the CHIP data are slightly different across years, we modify our identification strategies for on-job degree holders accordingly. In CHIP 2007, we obtain the actual years of actual work experience ex_{actual} based on the year of starting the current primary job and the year of starting the current occupation.[47] One problem, though, is that ex_{actual} will be underestimated if one changed both job and occupation, and then some individuals with a degree obtained through schooling while having a job may be misclassified and be considered holding a regular degree, as is the case for unemployment. Therefore, we refer to the additional information on the year of taking the most recent National College Entrance Examination (NCEE) to double check the accuracy of the sample. CHIP 13 data provides information on schooling while having a job as individuals report directly whether his/her degree at junior college/college level was obtained through adult education programs(including web-based education, correspondence colleges). We refer to both the new information and the same information on schooling attainment and work experience as in previous surveying years

[46] To reduce the potential identification error caused by the reporting discrepancy, we adopted a more conservative approach in identifying those received a degree while at work based on the data. More specifically, to ensure individuals completed the highest degree with a job for most of the time to degree, we put $s_2 \geq 2$ for on-job junior college degree and on-job graduate degree, $s_2 \geq 3$ for on-job 4-year college degree. The regression results with $s_2 > 0$ are similar but with a relatively smaller gap in schooling returns between a regular and an on-job degree.

[47] The time for the current primary job and current occupation may differ. We choose whichever earlier as the year of starting to work to estimate ex_{actual} . Therefore, the error in identifying on-job degree can only happen to those who have changed both job and occupation. We used additional information to mitigate this problem as shown in the Appendix B.

to determine whether the respondents completed the highest degree while having a job. More details are included in the Appendix B.

4.4 Features of On-job Schooling based on Micro Sample

Table 32 shows the summary statistics of the total sample and the sample who received a tertiary degree through on-job education. Consistent with our analysis using the macro data in Section II, the proportion of workers who received a tertiary education degree without quitting a job appears to be declining and remains stable after 2007. More specifically, in 1995, the proportion was 37.2%, and it fell to be 19.4% in 2013. As discussed in Section II, the relative demand for on-job education in China decreases with the increasing supply of regular graduates for the higher education expansion.

Most on-job students received their highest degree at junior college level. In 1995, 76.6% of the on-job junior college degree went to those who work and study at the same time, and the number dropped to 53.2% in 2013. The second largest group got an on-job degree at college level, with an increase from 19.2% in 1995 to 39.8% in 2013. Additionally, the share of individuals who completed an on-job graduate degree is around 4.2% in earlier years, but rises to 14.0% in 2007, and then drops to 7.0% in 2013. The statistics above show a changing picture that nowadays if a worker pursues a degree while at work he/she is more likely to go to a college or graduate program instead of a junior college program.

Table 32 – Variable Definitions and Descriptive Statistics-CHIP China

Variable	Definition	Total sample mean				On-job sample mean			
		1995	2002	2007	2013	1995	2002	2007	2013
a	Age	38.6	38.9	35.7	38.0	38.7	39.9	39.2	41.7
$Onjob$	1 if the highest degree completed on-job, 0 otherwise	0.372	0.330	0.185	0.194	1.0	1.0	1.0	1.0
s_2	Years of on-job schooling or job experience while schooling	-	-	-	-	3.57	3.31	3.29	2.47
s	Total years of schooling	14.3	14.5	15.1	15.0	14.8	15.1	15.6	15.3
Y	Hourly earnings(yuan)	3.9	7.1	17.8	23.3	3.9	7.2	17.1	23.5
Graduate	Graduate degree	0.022	0.022	0.062	0.054	0.042	0.037	0.140	0.070
College	4-year college	0.309	0.299	0.405	0.468	0.192	0.237	0.228	0.398
Junior College	3-year college	0.669	0.678	0.533	0.478	0.766	0.726	0.632	0.532
ex_{actual}	Actual years of work experience	18.9	18.6	12.3	15.6	21.5	22.1	20.3	22.1
Female	1 if female, 0 otherwise	0.351	0.396	0.436	0.446	0.372	0.424	0.454	0.459
Party	1 if communist party member, 0 otherwise	0.431	0.490	NA	0.376	0.494	0.574	NA	0.436
Married	1 if married, 0 otherwise	0.889	0.868	0.765	0.831	0.907	0.905	0.850	0.924
Permanent worker	1 if permanent contract worker, 0 otherwise	0.902	0.734	0.434	0.477	0.894	0.757	0.606	0.564
Long term worker	1 if long-term contract worker, 0 otherwise	0.082	0.154	0.467	0.310	0.091	0.149	0.325	0.291
Other workers	1 if temporary worker or short term contract worker, worker without contract, 0 otherwise	0.016	0.112	0.099	0.212	0.015	0.094	0.069	0.145
Technical worker	1 if professional personnel, 0 otherwise	0.464	0.399	0.395	0.365	0.402	0.344	0.369	0.331
Director of institution	1 if director of institutions, 0 otherwise	0.237	0.225	0.113	0.075	0.301	0.263	0.141	0.090
Office clerk	1 if office clerk, 0 otherwise	0.215	0.266	0.300	0.295	0.211	0.279	0.281	0.320
Other occupations	1 if skilled or nonskilled workers, salesclerk or service worker, etc., 0 otherwise.	0.084	0.110	0.193	0.141	0.085	0.114	0.209	0.152
Parent college education	1 if at least one of parents with college or above, 0 otherwise.	NA	0.179	0.198	0.152	NA	0.170	0.200	0.134
Max # of obs.		2485	2944	2280	3245	924	972	421	628

We compare the ranking of universities which offer regular degrees and on-job degrees in Table 33. CHIP 2002 contains information on the national rankings of the latest college where the individuals graduated. In CHIP 13, workers who graduated from college after 2000 report whether the college/junior college they graduated from is a 211 or 985 project college (nationally top universities) or not. Overall in 2002, there is some evidence that on-job students are more likely to attend lower ranking schools. On-job students on average went to similar ranking schools compared to regular students at junior college (72.7% vs 72.3%) and college (56.5% vs 52.3%) level. Yet, the proportion of on-job students attending low ranking schools at the graduate level is much higher than that for regular students (39.4% vs 23.3%). Similarly in CHIP 2013 we find that a higher proportion of working adults obtained college degrees from the non-985/211 project colleges compared to regular students, while the difference is negligible at junior college level.

Table 33 – School Ranking and Education Degree-CHIP China

Year	2002		2013	
Variable	Lower college ranking		Lower college ranking	
	On-job	Regular	On-job	Regular
Sample mean	0.651	0.615	0.947	0.825
Graduate	0.394	0.233	0.788	0.492
College	0.565	0.523	0.941	0.783
Junior college	0.727	0.723	0.979	0.956
No. of observations	604	1287	397	1666

Notes:

1. Lower college ranking in 2002: 1 if the latest college he/she graduated from is ranked average or below average, 0 otherwise.
2. Lower college ranking in 2013: 1 if the college/junior college isn't a 211 or 985 Project College, 0 otherwise.

Using our CHIP sample for working adults ages 18-60, we also compare the determinants, labor market, and educational consequences of the two types of higher education certification. Based on the CHIP 13 data, only 88.6% of those who obtained a college or three-year college degree while at work took the National Entrance Exam, while the share is 98.3% for the total sample. Furthermore, to view the student quality in two different education programs, we use high school grades in CHIP 2002 as an indicator. As reported in Table 34 for 2002, on-job students are slightly more likely to have had lower high school grades, but the gap is small, i.e., 26% vs. 21%, and the same situation happens at all education levels. In CHIP 2007, we use individuals' grades for their highest degree instead since the same information on high school grades is unavailable. There is an overall worse academic performance in the on-job group given a slightly larger proportion of students with lower grades. This may be related to the relatively lower admission requirements for tertiary education programs for working adults.

Table 34 – High School Ranking, High School Grades and Education Degree-CHIP China

Year	2002		2007	
Variable	Lower high school grade		Lower GPA	
	On-job	Regular	On-job	Regular
Sample mean	0.258	0.208	0.252	0.199
Graduate	0.111	0.100	0.203	0.048
College	0.156	0.119	0.135	0.129
Junior college	0.299	0.256	0.305	0.273
No. of observations	948	1947	421	1857

Notes: Lower high school grade equals 1 if the high school grade is ranked at middle 20%, lower 20% or lowest 20% of the class, 0 otherwise in CHIP 02. Lower GPA equals 1 if the grade at the latest school graduated is at average, below average, or is weak in CHIP 07, 0 otherwise.

The age distribution of students receiving tertiary education while having a job is reported in Table 35. In CHIP 07 and CHIP 13, we are able to estimate the starting age for junior college and college education.[48] We use the age of 21 years as a threshold, because in China most students are expected to graduate from college at age 21. As shown in Table 35 for 2007, older students dominate in the on-job student group. The majority of students in the regular education programs began their higher education at ages below 20 years, where a larger portion of the on-job students started after the age of 21 years. In CHIP 07, 31% of on-job students began junior college/college education at age 21 or above, while the proportion is drastically lower (12.0%) for regular students.

Table 35 – Starting Age and Higher Education Degree-CHIP China

Year	2007				2013			
Variable	Starting age				Starting age			
	Junior college		College		Junior college		College	
Age	On-job	Regular	On-job	Regular	On-job	Regular	On-job	Regular
Under 20	0.644	0.794	0.635	0.788	0.760	0.757	0.730	0.773
20-24	0.163	0.158	0.231	0.188	0.193	0.232	0.210	0.223
25-29	0.074	0.013	0.115	0.016	0.023	0.006	0.041	0.003
30 up	0.119	0.007	0.019	0.008	0.023	0.006	0.020	0.001
21 up	0.319	0.121	0.308	0.109	0.117	0.114	0.189	0.087
No. of observations	135	763	52	750	171	717	148	1032

Note: The starting age for junior college or college education is estimated based on the year of taking the most recent National College Entrance Examination.

More specifically, 7.4% of on-job junior college students were 25–29 years old, and 11.9% were 30 years old or more, while the numbers are 1.0% and 0.0% for those regular junior college students. However, in CHIP 13, there is very small difference between on-

[48] In CHIP 07 and CHIP 13, people reported the last time they took the National College Entrance Examination, and this is normally the time at which a student enrolls in college or university.

job students and regular students regarding the time to start their junior college education. Similarly, the share of workers who obtained a college degree while at work at the age 21 or above reduces to be 18.9%. It implies that working adults tend to start their college education at a younger age.

Among on-job degree earners, the proportion of female is slightly larger than that for regular students but the difference is quite small. Workers who obtained a tertiary degree while having a job are more likely to be members of the Communist Party. For example, in 2002, 57.4% of people with an on-job degree were party members, while only 44% of those with a regular degree were party members; and the numbers are 43.6% and 36.1%, respectively, in 2013. The party membership may have more advantage in pursuing schooling while at work.

Among labor market differences between the on-job degree earners and the regular degree earners, their average hourly earnings are generally comparable; as is shown in Table 1, the mean level of hourly (annual) earnings is 23.5(50508) yuan for those who obtained a tertiary degree while at work compared to 23.3(49742) yuan for the total sample in CHIP 2013. On-job degree earners tend to have much longer working experience for all sampling years, as expected. More specifically, among our CHIP 2013 samples, the mean level of actual work experience is 22.1 years, 6.5 years more than the average work experience of the total sample.

In addition, workers in some occupations may be more likely to pursue a degree while at work. Table 32 shows that people with an on-job degree are more likely to be employed with a permanent job and be head of institutions and office clerks. It is common in China that government officials and business executives obtain a higher education degree while at work. Individuals who aim for an on-job degree either pay for the program on their own, or they are sponsored by current employers. For example, employer sponsorship generally requires that the students return to the same employer after graduation, as in the so-called "Designated Training Program" ("Wei Pei" in Chinese); i.e., the employer designates some students to study for a graduate degree.

4.5 Empirical Investigation on the Equivalence between On-job and Regular Degrees

4.5.1 Empirical Model

We start with the human capital production function in the Mincer framework to model the difference between regular schooling and on-job schooling.[49] It assumes that individual human capital stock is accumulated through formal schooling and on-the-job learning, and then the amount of human capital of a worker with s years of schooling and ex years of labor market experience is:

$$h(s,ex) = e^{\phi(X)} e^{f(s)+g(ex)}, \qquad (1)$$

[49] The Mincerian human capital production function have been widely used in previous literatures like Bils and Klenow (2000), Caselli (2005) to estimate individual human capital stocks.

where X include variables that influence the quality of human capital such as schooling quality, early childhood human capital, etc.[50]

Assume an individual's earnings are represented by $w = W_0 \cdot h(s, ex)$, where W_0 is the wage rate per unit of human capital. W_0 is determined by the labor market structure as well as other factors that affect human capital productivity such as total factor productivity (Manuelli and Seshadri 2014). Therefore, individuals with a different amount of human capital have different earnings. By taking the logarithm and following the standard functional form for schooling, we get:

$$\ln(W_0 \cdot h(s, ex)) = \ln(W_0) + \beta s + g(\text{ex}) + \phi(X). \quad (2)$$

If we allow part of schooling years overlaps with one's job, i.e., on-job schooling, we can separate the total years of schooling into two parts, $s = s_1 + s_2$, where s_1 is the regular schooling years, s_2 is the years of on-job schooling, and then we get the following model:

$$\ln(w) = \ln(W_0) + \beta(s_1 + s_2) + g(a - s_1 - 6) + \phi(X), \quad (3)$$

with $\text{ex} = a - s_1 - 6$.[51]

---

[50] Based on an explicit income maximization problem where schooling and the age-earnings profile are endogenous, Manuelli and Seshadri (2014) provides a more general human capital acquisition model that explicitly controls for quality of schooling.
[51] Light (2001) extended the model to separate the in-school work experience before the students enter the job market and found that conventional models overstate the returns to "school only". We extend the model to investigate how the on-job education, the overlap of schooling years and work experience in lifetime, affect the returns to schooling. In US, Light (2001) found that the mean level of in-school experience is 1.1 years, while college graduates would have more than 2.8 years of experience. The special case in China is

Considering the possibility of different productivity in accumulating human capital from regular schooling vs. on-job schooling, i.e., the observed return to regular schooling differs from that of the on-job schooling, the model becomes:[52]

$$\ln(w) = \delta_0 + \beta s + (\beta' - \beta)s_2 + g(a - s_1 - 6) + \phi(X)\,. \qquad (4)$$

In general, the return to schooling is more likely to be discontinuous and is determined by the educational degrees. We then define a vector of educational degrees E based on the required years of schooling $\{e_i : i = 1, 2, ...k\}$:

$$S_D = (E_1 \cdot I(s = e_1) \quad E_2 \cdot I(s = e_2) \quad ... \quad E_k \cdot I(s = e_k))\,, \qquad (5)$$

where I is the indicator function. Therefore, equation (4) can be modified by changing the corresponding parameters into a vector:

$$\ln(w) = \delta_0 + S_D\beta + S_D\gamma \cdot I(s_2 > s_{2,Min}) + g(a - s_1 - 6) + \phi(X)\,, \qquad (6)$$

where $\gamma = \beta' - \beta$ represents the difference in returns to schooling between an on-job degree and a regular degree. If $\beta' = \beta$, there exists no difference between the returns to regular schooling and to on-job schooling; if $\beta' - \beta < 0$, the return to an on-job degree would be lower, indicating possibly less productive human capital accumulation.

---

the Chinese students don't normally work while in regular school, thus the overlap of schooling years and work experience reflects the on-job education.

[52] In most empirical work involving the Mincer model, the schooling parameter β is viewed as return to education, which will be affected by the market system. However, as can be seen in equation (1), the parameter represents the productivity of schooling in human capital production. To reconcile the above two perspectives, as shown in Manuelli and Seshadri (2014), human capital production is also affected by the market structure such as TFP and the quality of schooling. Therefore, our separation of regular schooling and on-job schooling is consistent with human capital production and market mechanism.

In estimating the above model, we need to specify a functional form for $g(ex)$. A complication is that for an individual with on-job schooling, there were s_2 years with both schooling and on-job learning. We can treat s_2 the same as other working years in human capital accumulation with regard to on-job learning, i.e., $g(a-s_1-6)=\theta_1(a-s_1-6)$, as in the standard Mincer specification, the total years of experience includes s_2.[53]

Another more general way is to allow the productivity of on-job human capital accumulation differs for regular working years and for working years while doing schooling, in particular, $g(a-s_1-6)=\theta_1(a-s_1-6)+\theta_2 s_2$, where θ_2 captures the different return to on-job learning while doing schooling at the same time.

4.5.2 Baseline Results

We first estimated the model (6) with education degrees, and report the ordinary least squares (OLS) results in Table 36.[54] The base samples are workers who obtained the highest degree at junior college level through regular programs. In all sampling years

[53] Note that we do not put the quadratic term of the experience here for simplicity. However, we include both linear and quadratic form for experiences in our empirical estimation.
[54] The number of individuals without urban citizenship is very small. We also ran all the regressions without the urban citizenship variable, and the results are similar. Here we do not control for urban citizenship to avoid multicollinearity issues.

except for 2007, there is no significant difference in the returns between on-job and regular degrees at junior college level and the signs are all negative. [55]

Table 36 – Basic Model-CHIP China

Year	1995	2002	2007	2013
Graduate	0.169*	0.425***	0.533***	0.558***
	(0.0904)	(0.0732)	(0.0764)	(0.0413)
College	0.130***	0.198***	0.200***	0.215***
	(0.0207)	(0.0230)	(0.0248)	(0.0200)
Graduate $\times$ *Onjob*	-0.0715	-0.241**	-0.295**	-0.138*
	(0.108)	(0.101)	(0.101)	(0.0739)
College $\times$ *Onjob*	-0.0937**	-0.104**	-0.0177	-0.0950**
	(0.0331)	(0.0352)	(0.0467)	(0.0314)
Junior college $\times$ *Onjob*	-0.0177	-0.0222	-0.0991**	-0.0416
	(0.0198)	(0.0211)	(0.0370)	(0.0297)
ex_{actual}	0.0226***	0.0237***	0.0323***	0.0306***
	(0.00386)	(0.00427)	(0.00433)	(0.00346)
ex^2_{actual}	-0.000246**	-0.000302**	-0.000567***	-0.000465***
	(0.0000889)	(0.000100)	(0.000118)	(0.0000921)
Female	-0.0184	-0.0367**	-0.161***	-0.148***
	(0.0170)	(0.0177)	(0.0224)	(0.0171)
Party	0.0474**	0.0751***	-	0.0106
	(0.0171)	(0.0183)		(0.0189)
Married	0.169*	0.0527	0.114***	0.0505*
	(0.0904)	(0.0339)	(0.0310)	(0.0267)
Constant	0.860***	1.343***	2.063***	2.414***
	(0.121)	(0.0823)	(0.0564)	(0.0428)
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Summary Statistics	R2= 0.420	R2= 0.334	R2= 0.343	R2= 0.309
	F=55.3	F= 38.42	F=39.45	F=40.39
	N=2485	N= 2944	N= 2280	N= 3245

Note:

1. The samples are full-time workers who completed the highest qualification at junior college, college, or graduate school level.
2. Robust standard errors are in the parentheses. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

[55] We tried to make stricter requirements on S_2: S_2 should be equal to or larger than the number of schooling years required for a regular degree, e.g. 4 years for college level education, 3 years for three year college and graduate level education. The results are consistent with the current results; the negative returns to on-job education mostly became even larger in magnitude. In CHIP 2002, the negative returns became statistically significant at all education levels. The results could be presented under request.

At college level, the returns to on-job schooling were significantly lower than that for regular schooling in 1995, 2002 and 2013. More specifically, in 2013(1995) the estimated return for an on-job college degree was 12.8 (3.7) % compared with that for a regular junior college degree, while the number was 24.0 (13.9) % for regular college graduates.[56] In addition, it seems that the gap in schooling returns between regular degree and on-job degree at college level follows a decreasing trend.

The difference between a regular and an on-job graduate degree is negative and significant for all the sampling years except for 1995. The gap is very large, accounting for 30–60% of the rate of return for a regular graduate degree, but it decreases with time, as is the case at college level. More specifically, the return for an on-job graduate degree was 20.1% in 2002, and increases to be 26.9% in 2007 and 52.2% in 2013; they are much lower than the return of 53% (2002), 70.4% (2007), 74.7% (2013) for a regular graduate degree, respectively. Moreover, there is an increasing value for an on-job graduate degree compared to the regular college degree, e.g., the return to an on-job graduate degree is only 73.8% of the return to a regular college degree in CHIP 95 and 93.3% in CHIP 02, but the ratios rose to be 1.2 in CHIP 07 and 2.2 in CHIP 13.

Meanwhile, the return to regular degrees keep rising, based on the narrowing gap in schooling returns between on-job degrees and regular degrees, it implies that the return to an on-job degree grows much faster than that of a regular degree in China. In particular, the return on a regular college degree rises continuously, reaching 24.0% in 2013. This result is consistent with findings in the literature (see, for example, Zhang, Zhao et al.

[56] For accuracy, we use $100\times(e^{\beta_k}-1)$ to calculate the percentages.

(2005)). The return to a regular graduate degree increases even faster than that of a regular college degree. From 1995 to 2013, these returns more than doubled, from 18.4% to 74.7%, with the regular junior college as baseline. Moreover, the gap between graduate degrees and other education degrees also increases across years, reflecting a strong demand for graduate degrees during the course of economic transition in China.

We tried a more general Mincer model by allowing a different impact of on-job learning with simultaneous schooling, i.e., the years of on-job schooling or job experience while schooling s_2 may have a different return. Table 37 shows consistent results with the basic model. However, the negative gap in schooling returns between a regular and an on-job degree became relatively smaller in magnitude. On-job learning with schooling has a negative impact on earnings because the estimates of θ_2 are negative across all sampling years, however, they are statistically insignificant except in CHIP 2002. Overall, the empirical evidence goes against the assumption that there exists significant different impact of on-job learning with simultaneous schooling. Results in CHIP 02 also indicate that there is a negative learning effect for schooling while at work, consistent with the previous results of negative schooling returns for on-job degrees. Furthermore, there exists high multicollinearity between the on-job education indicator $Onjob$, i.e. $I(s_2 > s_{2,Min})$, and the working experience while schooling, which equals to s_2. It makes the estimates of gap in schooling returns between a regular and an on-job degree statistically weaker. Based on the analysis above, we focus on the more parsimonious basic model for further analysis.[57]

[57] For example, in CHIP 2002, with the schooling portion of job experience included, the gaps between a regular and an on-job degree completed at college and graduate levels become statistically insignificant but

Table 37 – Basic Model allowing for Different Impact of On-job Learning with Simultaneous Schooling-CHIP China

Year	1995	2002	2007	2013
Graduate	0.169*	0.426***	0.533***	0.558***
	(0.0904)	(0.0733)	(0.0765)	(0.0413)
College	0.130***	0.198***	0.200***	0.215***
	(0.0207)	(0.0230)	(0.0248)	(0.0200)
Graduate $\times$ *Onjob*	-0.0640	-0.146	-0.277**	-0.133
	(0.118)	(0.113)	(0.122)	(0.0879)
College $\times$ *Onjob*	-0.0878*	-0.00958	0.000109	-0.0914**
	(0.0493)	(0.0587)	(0.0786)	(0.0457)
Junior college $\times$ *Onjob*	-0.0131	0.0456	-0.0861	-0.0386
	(0.0340)	(0.0397)	(0.0633)	(0.0393)
ex_{actual}	0.0226***	0.0235***	0.0323***	0.0306***
	(0.00386)	(0.00428)	(0.00433)	(0.00347)
ex^2_{actual}	-0.000245**	-0.000294**	-0.000566***	-0.000465***
	(0.0000888)	(0.000100)	(0.000119)	(0.0000924)
On-job schooling years s_2	-0.00142	-0.0229**	-0.00461	-0.00141
	(0.00822)	(0.0114)	(0.0171)	(0.0120)
Female	-0.0183	-0.0368**	-0.161***	-0.148***
	(0.0170)	(0.0177)	(0.0224)	(0.0172)
Party	0.0475**	0.0752***	-	0.0106
	(0.0171)	(0.0183)	-	(0.0189)
Married	0.162***	0.0529	0.114***	0.0505*
	(0.0335)	(0.0339)	(0.0311)	(0.0267)
Constant	0.860***	1.341***	2.062***	2.414***
	(0.121)	(0.0821)	(0.0565)	(0.0428)
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Summary Statistics	R2= 0.420	R2= 0.334	R2= 0.343	R2= 0.309
	F=53.6	F= 37.51	F=38.26	F=39.32
	N=2485	N= 2944	N= 2280	N= 3245

Note:

1. The samples only include individuals whose education levels are junior college, college, and graduate school.
2. Robust standard errors are in the parentheses. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

remain negative in signs. We also tried a more general model specification with both the schooling portion of work experience and its squared term included. Similar to the analysis above, higher multicollinearity will make some negative estimates of gap in schooling returns insignificant.

4.6 Unobserved Heterogeneity and Robustness Check

4.6.1 Proxy Variables for Unobserved Heterogeneity

To get a consistent estimate of return to schooling, we treat regular schooling and on-job schooling similarly when dealing with the well-known omitted ability bias and other unobserved heterogeneity that influence both the decision to pursue a degree and the decision to school while at work. For example, there may be some of the unobserved heterogeneity in individual motivation, ability, tastes of schooling, access to finance, etc. We first use the proxy variable approach to estimate the wage equations (6).

There are several aspects of the unobserved heterogeneity to consider for the on-job degree indicator $Onjob$. In particular, model (6) can be re-written as follows:

$$\ln(w) = \delta_0 + S_D \cdot \beta + S_D \gamma \cdot Onjob + g(a - s_1 - 6) + X\eta + \xi_j + q + \varepsilon \text{, (7)}$$

where w represents hourly earnings. ξ_j is unobserved job heterogeneity, and the variable q stands for individual unobservable, including ability, ambition, etc. ε is the idiosyncratic error.

One aspect of the unobserved heterogeneity is that some unobserved job characteristics may affect both the earnings and the decision to take on-job schooling. This is different from a traditional Mincer model where schooling has generally been completed before the job. For on-job schooling, the issue becomes much more complicated. For example, if one’s job is more challenging and requires additional education, the wage would be higher and the desire to get more education may be stronger. On the other hand, if one does not meet the job requirements, the wages will be lower but the pressure for getting additional education to catch up may be higher. On the employer's side, the management may push a worker to get more additional education either because they plan to promote the worker or require the worker to improve performance. Stenberg (2011) shows that it is difficult to improve the education of low-skilled worker both because employers are reluctant to train low skilled and because low skilled are unwilling to participate. Gicheva (2012) finds that job attachments are correlated with the probability of attending part-time graduate education. Montizaan, Cörvers and de Grip (2013) finds that workers with firm-specific skills are restrained in their work, and thus adult learning options may differ based on the institutions where they are employed. Therefore, it is likely that on-job schooling is correlated with unobserved job characteristics, i.e., something observed by the worker and/or the management, but not by econometrician. However, the direction of the bias caused by unobserved job heterogeneity is unclear.[58]

In order to remove or mitigate the potential effect caused by unobserved job heterogeneity ξ_j, we use job proxy to control for job traits based on occupation related information in the data. In this case, proxy variable is redundant to the model if job heterogeneity is included, and is to purge the correlation between on-job schooling and unobserved job heterogeneity.[59] In our model, the proxy for job includes occupations and the type of employment. The term "occupation" includes the occupation types such as

[58] This issue will be less a problem if the current job is not the same one when the individuals did the on-job studies, because the current job characteristics then should not relate to the decision for a continued education. However, the data show that less than 17% of individuals changed jobs after getting the aspired degrees.
[59] In this case, it is assumed that Z is a perfect proxy. If not, the bias still exists but may be smaller with Z included.

professional, head of institution, office clerk, general worker, or others. The “type of employment” has permanent contracts, under long-term contracts, and other work agreements. It is reasonable to believe that studying for a degree while having a job is related to the occupation of an individual and the type of employment.

Another potential issue is the well-known problem of omitted ability bias in the classical Mincer model. Then even with controls for job heterogeneity by occupation and employment type, the unobserved individual heterogeneity may still be correlated with the schooling choice and job proxy. In our case, α represents more than just ability, it could include ambition, self-discipline, etc. Therefore, all schooling variables will suffer the endogeneity problem, as they may be correlated with α.

However, the difference for our analysis is regarding unobserved individual heterogeneity α, in our models, we are interested in comparing those who obtained the same educational degree in regular studies vs. on-job studies. It is unlikely that obtaining the same degree at different times should not be correlated with individual unobservable, when controlling for the schooling variables (or education degrees), e.g., those who continued to a graduate program right after finishing college are more or less ambitious/able than those who went to a graduate program after starting work. Therefore, the variable $Onjob$ does not add additional endogeneity.

If highly motivated people just study on their own through more flexible on-job schooling rather than go for a regular degree, we would overestimate the effects of on-job schooling. Then, our estimates can be viewed as a lower bound of the difference between returns to a regular degree and returns to an on-job degree. On the other hand, lower returns to education for workers with an on-job degree may be due to the fact that people who decide to take a university degree along with a job are generally the people with low earning potential, and they either decide to go to study as they are not progressing in their current job and/or forced to gain more skills by their employer.

In this study, we use a proxy for the related individual unobservable, similar to those studies using IQ as the ability proxy. Traditionally, previous literature use parents' education as proxy for inherited ability. So we first add whether one of parents has a college education or above in the model as the first group of proxy variable.

In addition, those individuals possibly took on-job schooling because they were not accepted as regular students previously and thus less qualified on average. Therefore, we also control for student quality for the related individual unobservable. In CHIP 2002, individuals reported their grade ranking in high school. Based on Cyrenne and Chan (2012), students' high school grades are a strong predictor of their GPA in the university, and Grogger and Eide (1995) found a positive relationship between high school grades and earnings.[60] In CHIP 2007, we use individuals' grades for their highest degree as a proxy. Betts and Morell (1999) states that college GPA reflects human capital acquisition at a time when young adults are close to permanent entry into the labor force.[61] Many previous studies have found a positive link between GPA and subsequent earnings like Wise (1975), Jones and Jackson (1990), Loury and Garman (1995). To sum up, we control for information on academic performances to proxy student quality. A student is

[60] There is no grade information in CHIP 1995 data.

[61] The implication for college grades can be different from that for high school grades. The knowledge learned in high school may not be used directly in one's work. However, the knowledge and skills learned at junior college or above before going to the labor market may be closely related to one's work. Therefore, the grades may reflect both the student's quality and skills that affect one's job performance directly.

considered to be of lower quality if his/her high school grade ranking is in the lower 60 percentile of the class in CHIP 02; or if the grade at the latest school graduated is at average, below average, or is weak in CHIP 07.

The results adding job heterogeneity and grade proxy are reported in Table 38.[62] Comparing Table 36 and Table 38, we find that, with the inclusion of the job proxy, the returns to regular graduate and college degrees are lower. With the inclusion of the job proxy, the statistical significance of the difference between the returns to regular degrees and on-job degrees do not change much.[63] The magnitudes change in different directions. More specifically, for graduate degrees, the gaps are smaller in 2007 and 2013, but larger in 1995 and 2002. However, for college degrees, the gaps become smaller in all sample years. This result is consistent with our hypothesis that the direction of bias caused by job heterogeneity is ambiguous.

At the college and junior college level, it appears that unobserved job heterogeneity is negatively correlated with on-job schooling, i.e., the job heterogeneity that favors a choice for additional education on-job also tends to lower the wage level. For example, it is possible that those who "under-perform" in a job could be under higher pressure to catch up by obtaining additional schooling at college level. On the other hand, at the graduate level, job heterogeneity seems to be correlated with on-job schooling in either way.

[62] For the models with years of schooling, the results change very little.

[63] Except in CHIP 2013 the gap in return between on-job degree and regular degree at graduate level changed from negative significant to insignificant, the gap at college level became insignificantly positive in CHIP 2007.

The returns to regular schooling for both graduate and college degrees are all slightly lower for all the sampling years (except for CHIP 95 because it doesn't have available information for grades). Moreover, the gaps in returns to both graduate and college degrees are reduced for all sampling years, but the differences are relatively small. It indicates a possible negative correlation between on-job schooling and individual unobservable, i.e., individuals with relatively inferior academic grades or less parents' education are more likely to choose on-job education. There is a clear direction of the bias caused by individual unobservable, which differs from the ambiguous bias caused by job unobservable, as discussed above.

Table 38 – Models with Controls for Unobserved Heterogeneity-CHIP China

Year	1995	2002		2007		2013	
Graduate	0.146	0.421***	0.386***	0.461***	0.432***	0.476***	0.471***
	(0.0899)	(0.0689)	(0.0700)	(0.0741)	(0.0773)	(0.0416)	(0.0435)
College	0.119***	0.182***	0.171***	0.157***	0.136***	0.168***	0.163***
	(0.0212)	(0.0230)	(0.0234)	(0.0246)	(0.0257)	(0.0201)	(0.0208)
Graduate $\times$ *Onjob*	-0.0823	-0.270**	-0.261**	-0.261**	-0.264**	-0.104	-0.0952
	(0.109)	(0.0968)	(0.0973)	(0.0970)	(0.0993)	(0.0741)	(0.0800)
College $\times$ *Onjob*	-0.0898**	-0.0900**	-0.0887**	0.0164	0.0286	-0.0824**	-0.0777**
	(0.0335)	(0.0354)	(0.0354)	(0.0474)	(0.0483)	(0.0309)	(0.0312)
Junior college $\times$ *Onjob*	-0.0193	-0.0227	-0.0256	-0.0866**	-0.0807**	-0.0363	-0.0316
	(0.0199)	(0.0208)	(0.0212)	(0.0352)	(0.0358)	(0.0287)	(0.0295)
ex_{actual}	0.0219***	0.0205***	0.0207***	0.0230***	0.0228***	0.0236***	0.0221***
	(0.00392)	(0.00424)	(0.00433)	(0.00434)	(0.00451)	(0.00349)	(0.00366)
ex^2_{actual}	-0.0002**	-0.0003**	-0.00027**	-0.0004***	-0.0005***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.000102)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Permanent worker	-0.0532	0.234***	0.237***	0.305***	0.300***	0.225***	0.222***
	(0.0908)	(0.0362)	(0.0367)	(0.0454)	(0.0467)	(0.0280)	(0.0291)
Long term worker	-0.0248	0.236***	0.243***	0.195***	0.195***	0.197***	0.193***
	(0.0948)	(0.0394)	(0.0401)	(0.0416)	(0.0430)	(0.0249)	(0.0258)
Technical worker	0.0637*	0.0543*	0.0463	0.242***	0.233***	0.190***	0.189***
	(0.0344)	(0.0325)	(0.0334)	(0.0339)	(0.0345)	(0.0262)	(0.0269)
Director of institution	0.0253	0.0910**	0.0872**	0.293***	0.286***	0.170***	0.158***
	(0.0373)	(0.0360)	(0.0369)	(0.0474)	(0.0479)	(0.0349)	(0.0352)
Office clerk	-0.0224	0.0190	0.00979	0.111**	0.109**	0.0889***	0.0941***
	(0.0374)	(0.0332)	(0.0342)	(0.0346)	(0.0352)	(0.0251)	(0.0260)
Parent college education			0.0721**		0.0820**		0.0405*
			(0.0224)		(0.0279)		(0.0237)
High school grade			0.0225*				
			(0.0120)				
GPA					0.0562***		
					(0.0164)		
Constant	0.890***	1.271***	1.204***	1.678***	1.457***	2.145***	2.135***
	(0.154)	(0.0880)	(0.100)	(0.0677)	(0.0951)	(0.0486)	(0.0505)
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Summary Statistics	R2= 0.422	R2=0.351	R2=0.355	R2=0.382	R2=0.386	R2=0.344	R2=0.343
	F=47.11	F=36.49	F=34.2	F=39.46	F=36.57	F=40.46	F=37.54
	N= 2437	N= 2931	N= 2840	N= 2261	N= 2157	N= 3172	N= 2996

Notes: a.Personal characteristics like gender, ethnic minority, party membership, marriage status, and urban citizenship are controlled in the model. b. High school grade=5 if the high school grade is ranked at top 20%, 4 if higher middle 20%; 3 if middle 20%; 2 if lower 20%, 1 if lowest 20% of the class in CHIP 02. c. GPA=5 if the grade at the latest school graduated is very good; 4 if good; 3 if at average; 2 if below average; or 1 if weak in CHIP 07, 0 otherwise. d. Robust standard errors are in the parentheses. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

4.6.2 Instrumental Variable Estimation with Control Function Approach

Considering the job proxy and ability proxy may not perfect, we use the instrumental variable approach to address the potential unobserved heterogeneity, via the Control Function estimation (CF). As an alternative to the 2SLS, it relies on the same identification condition of valid instruments. However, in the case with nonlinear in endogenous variables, the CF approach offers some advantages in easier operation and efficiency. The basic idea is to use extra instruments to break the correlation between the choice of on-job schooling and unobservable affecting the on-job schooling choice, and then include the residual of on-job schooling as a control variable in the estimation of the wage equation. The residual can provide a straightforward test of the null hypothesis that on-job schooling choice is exogenous.

In CHIP 95 and 02, we use whether he/she had ever been an intellectual youth sent down to the countryside as a valid IV. Starting from 1955, ending in 1980, Chinese government had sent around 12-18 million urban educated youth, junior school, high school and college students, to go to poor rural areas for the youth "re-education", which delayed the student group's timing for regular higher education thus increased their probability of pursuing further education on-the-job.[64] As for its validity, Li (2003) finds that this unique experience has no significant effect on individuals' wages using CHIP 95; our empirical results in both CHIP 95 and CHIP 02 also support their results.

[64] Source: http://baike.baidu.com/link?url=LzpvNBNDZHEFCSiIfYnDFaC5J0Ds_oSStK_BE3VFe3pg5m-rrXQDxhgZ-dFZNQ68wiAdN8oijjCrOqwNFVV45asD3QR9OpGIYbrVxN9UbxlBIS_5Y5szOiKihu0o5JZW.

Financial constraint may be another reason for an individual to choose on-job education instead of a regular one. For example, individuals with poor family background have to start working rather than go to college, and then may return to college later while at work. Based on information availability, in CHIP 07 and 13, we used individuals' birth rank among siblings as IV for the on-job education choice. The argument is: the older among the siblings, he/she would be more likely to enroll in an on-job education, for example, the older brothers would have more incentive/pressure from the family to enter the labor market earlier and reduce the parents' financial burden, therefore they would be more likely the group who chose the on-job education programs. Also in CHIP 13, we have information on whether at least one of siblings held a higher education degree. The workers would have more incentive or peer pressure to pursue a higher education degree in whichever way.

Table 39 reports the estimates based on control function approach. The correlations between the choice of on-job education and the youth "re-education" dummy are 0.07 (significant at 5% significance level) in CHIP 95, and 0.04 (not statistically significant) in CHIP 02.

Also from the first stage results in Table 39, when you are born as an elder child, and have siblings who received a higher education degree, you are as expected more likely to choose high education while having a job. Based on the test of the predicted residual from on-job education choice in the model, the results cannot reject the exogeneity of schooling choice while at work after controlling for the job heterogeneity and individual ability with proxy variable approach. Therefore, it supports our previous analysis for the baseline results.

Table 39 – Estimates of Control Function Estimator with Education Degrees-CHIP China

Year	1995	2002	2007	2013
Second stage		Log(hourly wage)		
Graduate	0.0661	0.350*	0.559***	0.439***
	(0.122)	(0.197)	(0.165)	(0.0542)
College	0.172**	0.177***	0.0932**	0.166***
	(0.0594)	(0.0379)	(0.0420)	(0.0210)
Graduate $\times$ Onjob	0.228	-0.100	-0.786	0.206
	(0.327)	(0.812)	(0.552)	(0.323)
College $\times$ Onjob	0.222	0.0725	-0.513	0.226
	(0.308)	(0.809)	(0.551)	(0.316)
Junior college $\times$ Onjob	0.293	0.136	-0.627	0.272
	(0.311)	(0.809)	(0.552)	(0.313)
Predicted residual from first stage	-0.311	-0.161	0.548	-0.304
	(0.311)	(0.810)	(0.552)	(0.315)
Constant	0.799***	1.178***	1.533***	2.151***
	(0.178)	(0.164)	(0.128)	(0.0518)
Occupation type	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes
Parent education	No	Yes	Yes	Yes
High school grade	No	Yes	No	No
GPA	No	No	Yes	No
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Summary Statistics	F=45.93	F=33.48	F=31.92	F=36.59
	N=2412	N=2840	N=1900	N=2993
First stage		Onjob		
Re-educated youth	0.0687**	0.0361		
	(0.0277)	(0.030)		
Birth rank among siblings			-0.0167**	-0.0138**
			(0.00628)	(0.00678)
Sibling with college education or above				0.0603**
				(0.0202)
Summary Statistics	F=15.47	F=11.93	F=16.52	F=11.04
	N=2412	N=2840	N=1900	N=2993

Note:

1. Personal characteristics like gender, ethnic minority, party membership, marriage status, and urban citizenship are controlled in the model.
2. Robust standard errors are in the parentheses. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

4.7 What cause the Differences between On-job Degrees and Regular Degrees?

In the previous econometric estimations, we find significant differences in return between regular schooling and on-job schooling at college and graduate levels. The findings raised a number of interesting questions. For example, why is the return on a degree earned while having a job lower than that earned as a regular student? We will further investigate those issues based on information in the data.

4.7.1 School Quality

One possible explanation for the lower returns could be that the institutions, which offer on-job education programs, are relatively less prestigious, or have low quality. As a result, those on-job students receive training in programs that are not as good as their regular study counterparts in general. Grove and Hussey (2014) investigates the heterogeneity in quality characteristics and returns to MBA programs, and confirm that the quality of peers and schools may matter most for earnings. In general, low ranking schools have relatively fewer resources for students. Heckman, Layne-Farrar and Todd (1996) finds that school resources are positively related to the earnings. Moreover, high ranking schools attract high quality students and thus generate positive peer effect on other students (Ding and Lehrer 2007).

When we run the model by replacing on-job education with school ranking, the result (Table 40, column 2) shows that the ranking of the latest college he/she graduated actually has no significant impact on the rate of return in 2002.

Table 40 – Model with Control of School Ranking-CHIP China

Year	2002	2002	2013	2013
Graduate	0.437^{***}	0.302^{***}	-	-
	(0.0717)	(0.0591)	-	-
College	0.206^{***}	0.178^{***}	0.135^{***}	0.244^{**}
	(0.0281)	(0.0255)	(0.0298)	(0.0797)
Graduate $\times$ Onjob	-0.289^{**}			
	(0.103)			
College $\times$ Onjob	-0.108^{**}		-0.184^{**}	
	(0.0379)		(0.0659)	
Junior college $\times$ Onjob	-0.0144		-0.155^{**}	
	(0.0306)		(0.0771)	
Graduate $\times$ Lower college ranking		-0.104		-
		(0.195)		-
College $\times$ Lower college ranking		0.0600		-0.0814^{**}
		(0.0492)		(0.0401)
Junior college $\times$ Lower college ranking		0.0361	0.0315^{***}	0.0485
		(0.0338)	(0.00553)	(0.0744)
Experience	0.0170^{**}	0.0149^{**}	-0.000424^{**}	0.0309^{***}
	(0.00564)	(0.00558)	(0.000144)	(0.00549)
Experience squared	-0.000205	-0.000181	-0.000438^{***}	-0.000450^{**}
	(0.000132)	(0.000132)	(0.000131)	(0.000141)
High school grade	-0.0136	-0.0215		
	(0.0265)	(0.0270)		
Parent education			0.0392	0.0281
			(0.0358)	(0.0365)
Constant	1.321^{***}	1.335^{***}	2.204^{***}	2.169^{***}
	(0.107)	(0.108)	(0.0734)	(0.102)
Occupation type	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	1867	1867	1342	1342
R^2	0.328	0.324	0.358	0.355
adj. R^2	0.312	0.308	0.338	0.335

Notes:

1. Lower college ranking=1, if the most recent school graduated from ranked average or below national average; and 0 otherwise for CHIP 02. Lower college ranking=1 if the college/junior college doesn't belong to 211 or 985 project colleges, 0 otherwise in CHIP 13.
2. We restrict the samples in CHIP 2013 to those who obtained the highest degree at college or junior college level, and their graduation colleges/junior college belongs to the regular institution of higher education.
3. Personal characteristics like gender, ethnic minority, party membership, marriage status, and urban citizenship are controlled in the model.
4. Robust standard errors are in the parentheses. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

Since the on-job degrees could be offered by both regular colleges and adult education colleges, people may argue that the difference in schooling returns are mainly caused by the drastic difference in education patterns between regular colleges and adult education colleges. Therefore, we further restrict our sample in CHIP 2013 to those who obtained the highest degree at junior college or college level, and their graduation junior colleges/college are categorized as regular college. As for the results in 2013, if a worker got the degree at college level from a school which doesn't belong to 211 or 985 project colleges(lower college ranking), he/she will have a significant lower schooling return. However, it is much smaller than the estimated gap in schooling returns between an on-job degree and a regular degree at college level, which is 0.18% (Table 9, column 3), with the same sample. Therefore, the inferior schooling returns to an on-job degree offered by the regular colleges still exist and are much larger. Also, it cannot be fully explained by the quality of the school/program.

4.7.2 Learning Capacity with Age

Because the on-job students are generally older than regular students, another possible explanation for the lower return is aging. Aging is a general process of functional decline, which involves in particular the decline of cognitive abilities. Much research has analyzed the negative correlation between aging and learning, e.g. Vallée, Mayo and Le Moal (2001) and Eppinger, Kray et al. (2008). The learning capacity decelerates with aging, and this exerts some negative influences on human capital acquisition.

The regression results with control of age are reported in Table 41.[65] We found that in CHIP 07 and 13 the starting age has no significant effect on the schooling returns for workers with a regular degree and those with a degree earned without quitting the job.

However, the proportion of on-job students aspiring to a college degree at age 30 and more is small (2%) as shown in Table 35. It is unlikely that studying in the age 20-29 will have such a big difference in the learning effect.[66] In CHIP 2013, 19% of workers chose to pursue a college degree at the age of 21 or above, in contrast to 9% for regular graduates. It seems that starting the college education at age 21 or above has a negative and significant effect only for regular students while not for students who pursue a degree while at work. To sum up, we don't find clear evidence of a learning depreciation with age for on-job students.

To further investigate the effect of age, we also take the same age group from workers who obtained on-job and regular degrees. Around 8–12% of regular students began junior college or college at age 21 or above, and they may be individuals who were employed and then quit their jobs to enroll in a full-time regular education program. For workers who started college education at age 21 or above, we don't find significant gap in schooling returns between a regular degree and a degree earned while at work. It suggests on-job education may be an equivalent alternative to the regular education for adult workers who decide to postpone college education after age 21.

[65] The number of graduate students is too small in the sample to run the model with graduate students. For CHIP 95 and 02, age information is not available. Otherwise, a much in-depth investigation on the effect of age can be done.

[66] We also used other age thresholds and the results are similar. A caution note is that the sample size is small for both regular and on-job students.

Table 41 – Models with Age-CHIP China

Year	2007			2013		
	On-job sample	Regular sample	Total sample age 21+	On-job sample	Regular sample	Total sample age 21+
College	0.275**	0.171***	0.260**	0.0575	0.185***	0.134
	(0.113)	(0.0329)	(0.0929)	(0.0667)	(0.0292)	(0.0916)
College × Onjob			-0.0368			0.0893
			(0.137)			(0.146)
Junior college × Onjob			-0.0614			0.0405
			(0.114)			(0.112)
College × Age 21+	-0.0191	0.0768		0.106	-0.200***	
	(0.159)	(0.0710)		(0.136)	(0.0576)	
Junior college × Age 21+	0.0144	-0.0414		0.0373	-0.0729	
	(0.106)	(0.0666)		(0.100)	(0.0558)	
Experience	0.0163	0.0386***	0.0232*	0.0177	0.0412***	0.0376**
	(0.0183)	(0.00629)	(0.0137)	(0.0110)	(0.00511)	(0.0123)
Experience squared	-0.000287	-0.000871***	-0.000430	-0.000129	-0.000752***	-0.000515
	(0.000442)	(0.000214)	(0.000327)	(0.000273)	(0.000157)	(0.000318)
Female	-0.0767	-0.179***	-0.136*	-0.191**	-0.151***	-0.123*
	(0.0817)	(0.0306)	(0.0795)	(0.0599)	(0.0261)	(0.0735)
Parent education	0.0478	0.114**	0.0529	0.159	0.0400	-0.165
	(0.108)	(0.0373)	(0.108)	(0.104)	(0.0356)	(0.121)
Constant	1.908***	2.056***	1.968***	2.385***	2.432***	2.293***
	(0.264)	(0.0630)	(0.142)	(0.112)	(0.0408)	(0.112)
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
N	180	1448	216	296	1610	205
R^2	0.267	0.174	0.263	0.225	0.204	0.239
adj. R^2	0.214	0.167	0.220	0.192	0.198	0.192

Notes: 1. The samples only include junior college and college graduates. 2. The total sample includes the on-job sample and the regular sample that started higher education at age 21 or above. Robust standard errors are in the parentheses. 3. The stars ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively.

4.7.3 Different Earnings Path and Signaling Effects

The analyses above show that student quality, job heterogeneity, school quality, and aging are not likely to explain fully the lower returns to a degree earned while holding a job. The earnings gap could be caused by other factors, or a combination of the factors, including those we discussed.

One possible cause is the implicit cost-sharing mechanism for on-job schooling, which results in a different career earnings path. In particular, when an employer allows the employee to participate in a formal education program for a degree without quitting the job, they both understand that the performance on the current job may be affected, which will then incur implicit cost for the employer. In order to shift (partially or fully) the cost to the employee side, the employer may require the employee to take a pay cut, receive lower pay raises, drop a bonus or defer promotion, for example. Such an arrangement may result in a different wage path for the employee, and therefore a lower return on his/her on-job education. At the margin, the earnings gap can be fully recovered in the rest of employee’s career after getting the degree via on-job studies. However, this issue is more complicated, because the employee may not simply be looking at the normal returns to a degree he/she might pursue while working. Instead, he/she may only want to reach a better level than he/she is in the current employment by having obtained a higher degree than his/her current qualification. For example, if one has a junior college degree and decides to pursue a college degree, he/she may not expect the payoff for a regular college degree, but a better career and earning path than he/she has with the current degree. In this case, the implicit cost-sharing arrangement may achieve equilibriums at different earning paths, which could be lower than the marginal path for the full recovery of the investment.

The implicit cost-sharing mechanism on lifelong learning can be viewed as a market outcome. Although the return to an on-job degree is lower, it is still an optimal outcome negotiated between the employee and the employer. Yet, a policy that would reduce such costs on the employer side would help raise the return to an on-job degree. For example, the curricula for on-job degrees can be made more flexible so that the on-job students can adjust the course load based on-job needs in order to reduce the negative impact on work. Therefore, in addition to classes in the evening or weekends, modern Internet-based education makes conditions even more flexible and thus effective for lifelong learning. Many world-renowned research universities have joined in this learning revolution by offering online degree programs.[67] They deliver course material over an online platform and on-job students can access the same class material as the regular students, but at a more convenient time; modern technology can also make online courses comparable with face-to-face classes (Neuhauser 2002).

However, differing from the cost-sharing effect, another possible explanation for the earnings gap is the signaling effect**.** The labor market may have formed self-fulfilling skill expectations: since on-job degrees are "seen" to be inferior, they are provided with fewer opportunities of accelerating careers, which then results in less earnings. The

[67] For example, Georgia Institute of Technology is among pioneer universities offering on-line master's degrees by working with the online education provider Udacity. In fall 2013, 400 applicants were admitted to the first cohort of a massive online Master of Science in Computer Science program offered by its College of Computing, upon selection from a total of 2,361 applicants. The total number of applicants for this online master's program exceeded the total number of fall 2013 applicants to all of the college's on-campus MS programs. The online master's program aims to provide an elite computing education to "nontraditional students, such as working professionals, active military and others who need alternative models to continue their education". (*The Whistle,* Vol. 38, No. 25, December 9, 2013).

negative signaling of on-job degrees could originate from the possible fact that on-job degree students mostly studied in low-quality programs or they were mostly students with low quality. However, our data discussed above show that neither is the dominant case in China. This points to another less obvious possibility, i.e., that those on-job students in China did not engage in serious studies in the education program and that their records may not reflect the true academic performance. In other words, with the same degree, the effectiveness of learning may be very different between regular students and on-job students.[68] However, in the US, Darolia (2014) finds no evidence that students' academic grades are harmed by marginal work hours, when examining the effect of working on academic performance for full-time and part-time students. Therefobilre, in China, the difference could be caused by attitude, efforts, or institutional double academic standards for those two types of students.

The distrust of the labor market for on-job degrees has caused negative signaling. As a result, employers may scrutinize carefully to distinguish a degree earned regularly from a degree earned while holding a job, thus creating institutional barriers (or discrimination) for those who receive on-job degrees. This is especially the case in China, for example, in job recruiting, where many positions specifically require a regular degree of higher education and disqualify an on-job degree. Because labor markets are

[68] In China, it is a common view that many on-job students in higher education are privileged students, especially for attending on-job graduate program, because they are either government officials or company executives. Their main objective in getting a higher degree may be window dressing. Our data show that the on-job graduate degree holders are 14% more likely to be head of institutions than those with a regular graduate degree. Universities (and faculty members) may "trade" education degrees with them in order to acquire more resources. As a result, the academic records of those on-job students are likely to be cooked (or even fabricated) in a variety of ways. Such a phenomenal, so-called "academic corruption" in China was once so widespread that the Chinese government had to issue a serious warning on the subject and issued a regulation for on-job degrees in 2002. See the government regulation (in Chinese) at http://www.mos.gov.cn/flfg/cyfg/201310/t20131008_11280.html.

influenced by institutional and customs factors, such a signaling effect may affect the market valuation for an on-job degree, and then results in a lower valuation of such a degree. The signaling effect may be lasting due to asymmetric information, even if the on-job education program has corrected itself.

Clearly, if an on-job degree is distorted in its learning effects, then its value will be discounted by the market. Such a phenomenon can be detrimental to lifelong learning, as it will cause those who studied seriously to be treated unfairly. The outcome could be that serious students may become less likely to choose on-job education, and this would result in a vicious circle that would negatively affect the effectiveness of lifelong education systems for on-job degrees. Therefore, it is imperative for the Chinese government and institutions of higher education to tighten up the academic standards for all on-job students and put them in the same level field as regular students, in order to avoid the distortion of on-job degrees.

The difficulty, however, is that the cost-sharing effect and signaling effect may be mixed with each other, and the cost-sharing effect could be treated as signaling. In this case, even if the distortions in the on-job learning have been removed, the on-job degree may still be viewed as "inferior", and hence it will negatively affect the market opportunities for on-job degree holders.

4.7.4 Is it Worthwhile to Obtain a Degree while Having a Job?

To put the difference in returns into perspective, we transfer the gap into annual earnings. The benefit for on-job schooling is that the individual does not give up salary while attending the education program; the cost, however, is that the return is lower.

Using 2002 results (the third model in Table 29), the estimated return to regular and on-job graduate degrees is 49.5% and 14.7%, respectively; and for regular and on-job college degrees is 19.6% and 10.1%, respectively. At the graduate level, those with on-job graduate degrees would earn RMB 5,125 less annually.[69] However, the annual saving of earnings is approximately RMB 16,395, which is the average salary for those with a college degree.[70] This annual saving is approximately 3.2 times of the annual earnings gap. Depending on the discount rate, the total salary saved in three years of on-job graduate study (assuming a master's degree) could be worth approximately 10 years of the earnings difference caused by the lower return, using this simple procedure.[71] Similarly, for an on-job college degree, the estimated saving from non-forgone earnings in four years is approximately 29 years of the earnings gap.[72]

Based on the data, the average age for starting college with a job is around the age of 21.[73] In this case, the college degree will be received at age 25. Based on the above estimates for 2002, the saving through non-forgone wages can almost cover the earnings difference caused by lower returns until age 54, which is quite near the retirement age (the legal retirement age in China is 60 for men and 55 for women). Therefore, it is likely that on-job schooling for a college degree is as efficient as regular study, even with a

---

[69] It is calculated based on the formula, $\left[1-\exp(\beta_{edu\cdot onjob})\right]\cdot avearnings$, where $\beta_{edu\cdot onjob}$ represents the coefficient of the interaction term for each educational degree, and *avearnings* is average annual earnings for those who received a regular degree.

[70] During on-job education programs, individuals may receive only basic wages and/or receive no raise, bonuses, etc. For simplicity, we ignore this issue here.

[71] In terms of present value, the saving from non-forgone earnings occurs earlier than the higher earnings with a graduate degree when the salary gap starts, and thus should be discounted less.

[72] In 2007, the total earnings saved via on-job studying for three years of a graduate program are approximately 11 years of the earnings gap. For an on-job college degree in 1995, the estimated saving from non-forgone wages in four years of college studies is approximately 39 years of the earnings gap.

[73] The age information is only available in CHIP 2007 and CHIP 2013.

lower return. For graduate degrees, however, the saving is unlikely to cover the lifetime earning differentials, since the individual would not stop working at 35 years old.[74]

Clearly, there is a trade-off for an individual to choose on-job tertiary education. On the one hand, a higher degree obtained while at work raises the earnings, and thus, the earlier a higher educational degree is obtained on-job, the higher lifetime income would be. On the other hand, the on-job degree has a lower return relative to a regular degree, and thus the earlier one receives an on-job degree, the larger the lifetime earnings gap compared to that for an equivalent level of regular degree.[75]

4.8 Conclusions and Policy Implications

As the proportion of older individuals in China (and in many other industrialized countries) is increasing rapidly, and as knowledge and technology are also advancing at a fast rate, lifelong learning is becoming increasingly important in maintaining a qualified labor force with updated human capital. We investigate the effects of degree programs for full-time workers, using four waves of CHIP survey data for the years 1995, 2002, 2007 and 2013.

We find that in the sample period, a significant proportion of working individuals received their tertiary degrees while at work, and on-job students increasingly pursued higher education degrees. We find a significant difference in the returns to education

[74] Based on CHIP 07, the average age for starting an on-job graduate program is 25 and the oldest age is 45.
[75] Another approach for comparison is to calculate the internal rate of return (IRR) for a regular degree and an on-job degree. Because the calculation involves many additional assumptions, it is out of scope of this study.

between regular students and on-job students. In particular, the rate of return for an on-job graduate degree is approximately 25-28 percentage points lower than that for a regular graduate degree. For a four-year college degree, the return to on-job learning is 7-9 percentage points lower than that for regular learning. However, there is no significant gap between returns to on-job and full-time schooling junior college degrees. The gap in return increases with the education level, and it is quite sizeable. Our regression results are quite robust to various specifications and estimation methods.

We find no evidence that school quality or aging are the dominant factors for the gap in returns. Other possible explanation such as cost-sharing effect and signaling effect are discussed. Additionally, our simple estimates show that the "income savings" due to non-forgone wages while maintaining a job throughout a study program can generally recover the lifetime earnings gap caused by the differing returns on the college degree, though this is generally not the case for an on-job graduate degree.

In order to improve the efficiency of lifelong learning in general, and schooling while at work in particular, policies should aim at reducing the implicit cost for employers to arrange for their employees to study, by providing more flexibility in the schooling, and aim at encouraging more transparency regarding degrees earned while holding a job. However, the ultimate success of on-job education is determined by the enforcement of the same rigorous academic standard that is applied for regular students. We believe that modern, internet-based distance learning can provide an effective mechanism to accomplish these goals, both in terms of providing more flexibility for on-job students and by implementing the same learning requirements and standards as for regular students.

4.9 Appendix B: Identifying On-job Degrees in CHIP 07 and CHIP 13 Data

For CHIP 07, ex_{actual} is based on the year of starting the current primary job (T_1) or occupation (T_2), that is $ex_{actual} = 2008 - \min(T_1, T_2)$, and 2008 is the year of reported information.[76] We identify the on-job degrees as follows:

When $s_2 = ex_{actual} - ex_{potential} \geq 0$, given that $ex_{potential}$ would correctly measure the potential work experience after regular education, it indicates that there is not an underestimation of ex_{actual} and individuals didn't change both their current job and current occupation, therefore we follow the same procedure for CHIP 95 and 02.[77]

On the other side, when $s_2 = ex_{actual} - ex_{potential} < 0$, individuals may have changed both jobs and occupations, then, the ex_{actual} would be underestimated based on years of starting working for the current primary job or occupation. We utilize additional information on the year of taking the most recent National College Entrance Examination (NCEE) in China (T_3) to identify an on-job degree, because in general the year of taking the NCEE is the year when junior college or college education started.

More specifically, an individual with the highest degree completed at junior college level did the study while having a job, if $\min(T_1, T_2) - T_3 \leq 1$, i.e., the job began at most

---

[76] http://www.ciidbnu.org/chip/chips.asp?year=2007.

[77] One complication is that if an individual quitted from their current job for a full-time study at school, and return to the original job, then the calculated ex_{actual} would be an overestimation and will result in putting someone with a regular degree as having an on-job degree. It should strengthen our results.

one year after the junior college started, and thus $s_2 \geq 2$, there are at least two years of overlapping studies and work. Similarly, an individual has an on-job 4-year college degree if $\min(T_1, T_2) - T_3 \leq 1$, i.e., $s_2 \geq 3$. An individual has an on-job graduate degree, if $\min(T_1, T_2) - T_3 \leq 4$.[78] It normally takes a minimum of six years to complete a graduate degree (4 years of college plus 2.5-3 years of graduate study), thus the usual year gap between taking college entrance examination and starting work is 6 years. So, if the gap is equivalent to or less than 4 years, $s_2 \geq 2$, i.e., there must be at least 2 years' overlap between graduate study and work.

CHIP 13 provides more information for identifying on-job degrees. The information on on-job degrees is reported directly by individuals who completed the highest degree at junior year college or college level in year 2000 or later. For individuals who graduated from junior college/college earlier than 2000, and those with the highest qualification completed at graduate level, we follow the similar identification methods in previous sampling years as below:

a We estimate $ex_{actual} = 2008 - T_4$, where T_4 is the year to start the first job. T_4 is directly reported by the household heads and spouses, and other household members whose current job is their first job.[79] Then we follow the same identification procedure in CHIP 95 and CHIP 02.

[78] In China, the general requirement to get into a graduate program is a 4-year college degree. Therefore, if the time difference is 4 years, it implies that the individual started the job and a graduate program simultaneously right after completing college.

[79] In CHIP 13, the information on the entire work history is available for the majority of the regression samples. The household head/spouse sample reported the starting years of their first, second, and the last job before the current job, they takes up 74.3% of the regression sample. Among the non-household

b We follow the same identification method for CHIP 2007 and use the year of taking the most recent National College Entrance Examination (NCEE) (T_3) to identify on-job degrees for household members who are not household head/spouse and also have multiple jobs.

head/spouse samples, 79% of them reported their current job was their first job. Because the year gaps between jobs are very small, we used the starting year of the first job to calculate ex_{actual}.

CHAPTER 5 CONCLUSIONS-WHAT HAVE WE LEARNED

The dissertation analyzes the relationship of on-job learning and human capital accumulation. We investigates two types of on-job learning: on-job learning by doing and on-job schooling. Chapter 2 demonstrates the contribution of job tasks to an individual's traditional cogntive skills, measured by literacy and numeracy skills. More specifically, solving complex problems for at least once a month accounts for a 3-4th percentile increase in cognitive skills. The additional effect associated with complex analytical tasks relative to holding a general complex job is a 2th percentile increase in the skill distribution. Interactive tasks at work do not have a significant effect on cognitive skills.

However, comparatively those effects of on-job learning through tasks are also much smaller than those from early investments. The contribution of different sources of investments on cognitive skills follows a decreasing trend with their timing, and this is consistent with Heckman and Kautz (2013)'s analysis that cognitive skills are more malleable in early investments and much harder to accumulate in adulthood.

Chapter 3 demonstrates the contribution of job tasks to an individual's problem-solving skills. Problem-solving skills are comparatively more mallable and more likely to accumulate through on-job learning by doing with tasks. Estimates using problem-solving skill measures indicate that workers with a complex job can accumulate their problem-solving skills more. In particular, solving complex problems for at least once a month accounts for a 4th-6th percentile increase in the skill distribution. The additional effect associated with a complex analytical task relative to a general complex job is a 3th-

11th percentile increase in the skill distribution, while interactive job tasks do not have a significant effect. Our findings on complex problem-solving skills also show that task complexity can also contribute to a higher level of problem-solving skills but with a much smaller magnitude.

Our results show that workers can improve their skills with dealing with complex tasks at work. Improving workers' skills or quality helps raise the workers' productivities and firms' profits in the long run, and it is critical to a country's development. Therefore, our results provide important policy implications on the design of a national skill development system. More specifically, one way to improve workers' skills is government promote policies to reduce the unemployment rate, so that they have an opportunity to learn at work. Companies can improve their workers' quality by changing the task composition at work and increasing the complexity of job tasks performed by their employees.

In Chapter 4 we investigate the effects of degree programs for full-time workers, using four waves of CHIP survey data for the years 1995, 2002, 2007 and 2013. We find that in the sample period, a significant proportion of working individuals received their tertiary degrees while at work, and on-job students increasingly pursued higher education degrees. We find a significant difference in the returns to education between regular students and on-job students. In particular, the rate of return for an on-job graduate degree is approximately 25-28 percentage points lower than that for a regular graduate degree. For a four-year college degree, the return to on-job learning is 7-9 percentage points lower than that for regular learning. However, there is no significant gap between returns to on-job and full-time schooling junior college degrees. The gap in return increases with the education level, and it is quite sizeable.

Our results shed some light on how to improve the mechanism of on-job education. Firstly, we can reduce the implicit cost for employers to arrange for their employees to study, by providing more flexibility in the schooling. Simultaneously, the enforcement of the same rigorous academic standard for regular students should be applied to on-job students. An effective mechanism could be the modern, internet-based distance learning.

REFERENCES

Acemoglu, Daron and David Autor (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings." Handbook of labor economics **4**: 1043-1171.

Autor, David H, Frank Levy and Richard J Murnane (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration." Quarterly Journal of Economics: 1279-1333.

Avdic, Daniel and Marie Gartell (2015). "Working While Studying? Student Aid Design and Socioeconomic Achievement Disparities in Higher Education." Labour Economics **33**: 26-40.

Belanger, Paul and Albert Tuijnman (1997). "The “Silent Explosion” of Adult Learning." New patterns of adult learning: A six-country comparative study: 1-16.

Ben-Porath, Yoram (1967). "The Production of Human Capital and the Life Cycle of Earnings." Journal of political economy **75**(4, Part 1): 352-365.

Bils, Mark and Peter J Klenow (2000). "Does Schooling Cause Growth?" American Economic Review **90**(5): 1160-1183.

Black, Sandra E and Alexandra Spitz-Oener (2010). "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." The review of economics and statistics **92**(1): 187-194.

Blackburn, McKinley and David Neumark (1992). "Unobserved Ability, Efficiency Wages, and Interindustry Wage Differentials." Quarterly Journal of Economics **107**(4): 1421-1436.

Botero, Juan C, Simeon Djankov, Rafael La Porta, Florencio Lopez-de-Silanes and Andrei Shleifer (2004). "The Regulation of Labor." Quarterly Journal of Economics **119**(4): 1339-1382.

Cameron, Stephen V and James J Heckman (1993). "The Nonequivalence of High School Equivalents." Journal of labor economics **11**(1, Part 1): 1-47.

Cascio, Elizabeth, Damon Clark and Nora Gordon (2008). "Education and the Age Profile of Literacy into Adulthood." Journal of Economic Perspectives **22**(3): 47-70.

Caselli, Francesco (2005). "Accounting for Cross-Country Income Differences." Handbook of economic growth **1**: 679-741.

Cunha, Flavio and James Heckman (2007). "The Technology of Skill Formation." American Economic Review **97**(2): 31-47.

Cunha, Flavio, James J Heckman and Susanne M Schennach (2010). "Estimating the Technology of Cognitive and Noncognitive Skill Formation." Econometrica **78**(3): 883-931.

Cyrenne, Philippe and Alan Chan (2012). "High School Grades and University Performance: A Case Study." Economics of education review **31**(5): 524-542.

Darolia, Rajeev (2014). "Working (and Studying) Day and Night: Heterogeneous Effects of Working on the Academic Performance of Full-Time and Part-Time Students." Economics of education review **38**: 38-50.

Davidson, Janet E and Robert J Sternberg (2003). The Psychology of Problem Solving, Cambridge university press.

Deming, David J and David Figlio (2016). "Accountability in Us Education: Applying Lessons from K–12 Experience to Higher Education." Journal of Economic Perspectives **30**(3): 33-55.

Ding, Weili and Steven F Lehrer (2007). "Do Peers Affect Student Achievement in China's Secondary Schools?" The review of economics and statistics **89**(2): 300-312.

Eppinger, Ben, Jutta Kray, Barbara Mock and Axel Mecklinger (2008). "Better or Worse Than Expected? Aging, Learning, and the Ern." Neuropsychologia **46**(2): 521-539.

Freeman, Richard and Ronald Schettkat (2001). "Skill Compression, Wage Differentials, and Employment: Germany Vs the Us." Oxford Economic Papers **53**(3): 582-603.

Gansow, Jan (2002). "The American and German Educational Systems: A Comparison."

Gathmann, Christina and Uta Schönberg (2010). "How General Is Human Capital? A Task-Based Approach." Journal of labor economics **28**(1): 1-49.

Gicheva, Dora (2012). "Worker Mobility, Employer-Provided General Training, and the Choice of Graduate Education." Labour Economics **19**(2): 232-240.

Goos, Maarten and Alan Manning (2007). "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." The review of economics and statistics **89**(1): 118-133.

Goos, Maarten, Alan Manning and Anna Salomons (2009). "Job Polarization in Europe." American Economic Review **99**(2): 58-63.

Goos, Maarten, Alan Manning and Anna Salomons (2014). "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." American Economic Review **104**(8): 2509-2526.

Grogger, Jeff and Eric Eide (1995). "Changes in College Skills and the Rise in the College Wage Premium." Journal of Human Resources: 280-310.

Grove, Wayne A and Andrew Hussey (2014). "Returns to Mba Quality: Pecuniary and Non-Pecuniary Returns to Peers, Faculty, and Institution Quality." Labour Economics **26**: 43-54.

Hanushek, Eric A, Guido Schwerdt, Simon Wiederhold and Ludger Woessmann (2015). "Returns to Skills around the World: Evidence from Piaac." European Economic Review **73**: 103-130.

Hanushek, Eric A, Guido Schwerdt, Simon Wiederhold and Ludger Woessmann (2017). "Coping with Change: International Differences in the Returns to Skills." Economics Letters **153**: 15-19.

Hanushek, Eric A and Ludger Woessmann (2008). "The Role of Cognitive Skills in Economic Development." Journal of economic literature **46**(3): 607-668.

Hanushek, Eric A and Ludger Woessmann (2011). The Economics of International Differences in Educational Achievement. Handbook of the Economics of Education, Elsevier. **3:** 89-200.

Häusser, Jan Alexander, Stefan Schulz ‐ Hardt, Thomas Schultze, Anne Tomaschek and Andreas Mojzisch (2014). "Experimental Evidence for the Effects of Task Repetitiveness on Mental Strain and Objective Work Performance." Journal of Organizational Behavior **35**(5): 705-721.

Heckman, James J, John Eric Humphries and Tim Kautz (2014). "The Economic and Social Benefits of Ged Certification." The myth of achievement tests: The GED and the role of character in American life: 268-289.

Heckman, James J and Tim Kautz (2013). Fostering and Measuring Skills: Interventions That Improve Character and Cognition, National Bureau of Economic Research.

Heckman, James, Anne Layne-Farrar and Petra Todd (1996). "Human Capital Pricing Equations with an Application to Estimating the Effect of Schooling Quality on Earnings." The review of economics and statistics: 562-610.

Jepsen, Christopher, Peter Mueser and Kenneth Troske (2016). "Labor Market Returns to the Ged Using Regression Discontinuity Analysis." Journal of political economy **124**(3): 621-649.

Jones, Ethel B and John D Jackson (1990). "College Grades and Labor Market Rewards." The Journal of Human Resources **25**(2): 253-266.

Klein, Gary (1999). Sources of Power: How People Make Decisions, The MIT Press.

Krueger, Alan B (1993). "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989." Quarterly Journal of Economics: 33-60.

Li, Haizheng (2003). "Economic Transition and Returns to Education in China." Economics of education review **22**(3): 317-328.

Li, Haizheng (2010). Higher Education in China: Complement or Competition to Us Universities? American Universities in a Global Market, University of Chicago Press: 269-304.

Light, Audrey (2001). "In-School Work Experience and the Returns to Schooling." Journal of labor economics **19**(1): 65-93.

Lohmar, Bridgette and Thomas Eckhardt (2014). The Education System in the Federal Republic of Germany 2012/2013: A Description of the Responsibilities, Structures and Developments in Education Policy for the Exchange of Information in Europe. Bonn: Secretariat of the Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany.

Loury, Linda Datcher and David Garman (1995). "College Selectivity and Earnings." Journal of labor economics **13**(2): 289-308.

Manuelli, Rodolfo E and Ananth Seshadri (2014). "Human Capital and the Wealth of Nations." The American Economic Review **104**(9): 2736-2762.

Montizaan, Raymond, Frank Cörvers and Andries de Grip (2013). "Training and Retirement Patterns." Applied Economics **45**(15): 1991-1999.

Neuhauser, Charlotte (2002). "Learning Style and Effectiveness of Online and Face-to-Face Instruction." The American Journal of Distance Education **16**(2): 99-113.

OECD (2012). Literacy, Numeracy and Problem Solving in Technology-Rich Environments: Framework for the Oecd Survey of Adult Skills, OECD Publishing.

Pfeiffer, Friedhelm and Karsten Reuß (2008). "Age-Dependent Skill Formation and Returns to Education." Labour Economics **15**(4): 631-646.

Pischke, Jörn-Steffen (2001). "Continuous Training in Germany." Journal of population economics **14**(3): 523-548.

Riphahn, Regina T and Michael Zibrowius (2016). "Apprenticeship, Vocational Training, and Early Labor Market Outcomes–Evidence from East and West Germany." Education Economics **24**(1): 33-57.

Sabia, Joseph J (2009). "School-Year Employment and Academic Performance of Young Adolescents." Economics of education review **28**(2): 268-276.

Schönberg, Uta (2007). "Wage Growth Due to Human Capital Accumulation and Job Search: A Comparison between the United States and Germany." Industrial and Labor Relations Review **60**(4): 562-586.

Spitz-Oener, Alexandra (2006). "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure." Journal of labor economics **24**(2): 235-270.

Stenberg, Anders (2011). "Using Longitudinal Data to Evaluate Publicly Provided Formal Education for Low Skilled." Economics of education review **30**(6): 1262-1280.

Vallée, Monique, Willy Mayo and Michel Le Moal (2001). "Role of Pregnenolone, Dehydroepiandrosterone and Their Sulfate Esters on Learning and Memory in Cognitive Aging." Brain Research Reviews **37**(1-3): 301-312.

Wise, David A (1975). "Academic Achievement and Job Performance." The American Economic Review: 350-366.

Wooldridge, Jeffrey M (2010). Econometric Analysis of Cross Section and Panel Data, MIT press.

Xiao, Jin (2002). "Determinants of Salary Growth in Shenzhen, China: An Analysis of Formal Education, on-the-Job Training, and Adult Education with a Three-Level Model." Economics of education review **21**(6): 557-577.

Yamaguchi, Shintaro (2012). "Tasks and Heterogeneous Human Capital." Journal of labor economics **30**(1): 1-53.

Zhang, Junsen, Yaohui Zhao, Albert Park and Xiaoqing Song (2005). "Economic Returns to Schooling in Urban China, 1988 to 2001." Journal of comparative economics **33**(4): 730-752.